Essays on Asset Pricing and Political Risk

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Abstract

Some financial assets experience higher average returns than others. Asset-pricing theory suggests that this is due to the amount of systematic risk of that particular asset: the riskier the asset, the higher the average return. I hypothesize that one of these systematic risk factors is political risk, the result of political uncertainty. This dissertation examines the effect of political risk, in the form of terrorism risk and political regime change risk, on asset prices using linear factor asset pricing models. I find that terrorism risk is a significantly priced risk factor for nonindustry portfolios from January 1971 through December 2010. Results, however, differ when the data is divided into time periods before and after September 11, 2001, with the latter period indicating no risk from terror attacks. I further analyze the determinants of terrorism finding that social and geographic variables contribute more to terror activity than economic variables. I discover that political regime change risk is a nontrivial risk factor from 1927 through 2009, though risk premia results are smaller from industry returns than returns organized based on firm size and book-equity to market-equity. I also find that average excess returns are larger when the government is under the control of the Democratic party rather than for the Republican party for that same time period. Both sets of risk premia are ascertained by regression-based and nonlinear estimation methodologies. I investigate the small sample properties of two cross-sectional regression methods, ordinary and generalized least squares, and two generalized method of moments estimators, two-step and iterative. Using monte carlo simulations, I determine that the least squares regression methods outperform the generalized method of moments estimation procedures in terms of rejection rates and point estimates in small samples.

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Chapter 1

Introduction

There is a longstanding relationship between politics and the financial markets. But does political risk, which is based on the uncertainty over the ramifications of possible government actions and policies, have a direct affect on asset prices? This dissertation examines that very question. I hypothesize that political risk, the result of political uncertainty, is a contributing risk factor in the pricing of securities. I price this factor by creating two variables that proxy for political risk and then perform regression-based and nonlinear analyses to examine the risk premia incurred. In general, few factors have been accepted as having an effect on asset prices wherein investors require compensation for holding securities that contain this risk. This investigation supports the argument that political risk is an important factor that cannot be overlooked in the pricing of assets.

I examine the effect of political risk, in the form of terrorism risk and political regime change risk, on securities pricing. Terrorism risk can be indicative of underlying political unrest and uncertainty. The connection between terrorism and economic, political, and social unrest is a topic of much interest in the time since the September 11, 2001 terror attacks on the World Trade Center and the Pentagon. Unfortunately, little research focuses on the economic determinants, or the economic conditions and factors, that contribute to the incidence of terrorism (see Abadie (2006), Blomberg, Hess, and Weerapana (2004), Piazza (2006), and Tavares (2004)). But the research that does exist indicates that there is a significant relationship between economic factors (such as country income, unemployment, and economic growth), social factors (such as population, income disparity, and political freedom), and the number of terrorist events worldwide. These results imply that terrorist activity is indicative of larger problems with the economic and political fundamentals. If terrorism is indeed indicative of greater economic and political discontent, then it can be used as a proxy for political uncertainty. So it is in this context that I assess terrorism risk.

In Chapter 2, I hypothesize that terrorism risk, as a proxy for underlying political risk, is priced and I discover that this price is significant and positive. I institute a terrorism risk index based on the number of terrorist events that occurred within the United States between January 1971 and December 2010. I then perform analysis with a standard multifactor asset pricing model using both regression-based and generalized method of moments estimation techniques to examine the terrorism risk premium. Results suggest terrorism risk is priced in U.S. financial markets for nonindustry portfolios and the associated risk premium is positive and significant. However, separating the data into time periods before and after September 11, 2001 generates differing results. I discover that terrorism risk is not priced in the time after 9/11. I further examine the country-level determinants of terrorism using data on 148 countries from 1990-2008. Using Hausman-Taylor estimation, I find that social variables such as education levels and democracy variables have more of an affect on terrorism than economic variables like country income and employment rates.

It is difficult, if not impossible, to measure political risk. While uncertainty about particular government policies and the related costs are not easy to quantify, it is possible to measure political regime change. Though we cannot be certain which policies will be chosen nor the political costs of those policies, if we learn which regime is in control of the government at the time of the policy change, we will have some indication as to what type of policy is more likely and thus what type of costs to anticipate. In the third chapter, I investigate political risk in the form of political regime change. Using 25 portfolios organized on size and book-to-market equity and 49 industry portfolios, I determine that average excess returns are higher when the federal government is under the control of the Democratic Party rather than the Republican Party. I hypothesize that this is due to the switching of control of the federal government from Republican to Democrat and I create a proxy for political risk using a dummy variable that accounts for this political regime change. I then estimate the risk premium using cross-sectional regression and nonlinear least squares. Using returns data from 1927 through 2009, I determine that the risk premium for this factor is significant and positive and that political regime change, along with the Fama-French factors, explains well the variation in the cross section of nonindustry returns.

Chapter 4 is a comparison of the common methods used to estimate linear factor asset pricing models, the means by which I investigate political risk. Using the beta-representation of the linear factor asset pricing model, I compare regression-based and generalized method of moments estimation techniques using simulated data. I analyze each method under two specifications in small samples. Previous research indicates that while regression-based estimation does not account for heteroskedasticity or serial correlation, it is the most robust technique to use in larger samples. GMM estimation, on the other hand, does account for heteroskedasticity and serial correlation, but tends to perform poorly when the time series is small relative to the number of assets.

In Chapter 4, I generate twenty-five excess returns using factors simulated to mimic the political regime change dummy factor and excess market return factor from Chapter 3. In terms of power and point estimates, I find that the least squares regressors, ordinary and generalized, outperform the generalized method of moments estimators, two-step and iterative. While, in general, the least squares methods are preferred to GMM, GLS tends to perform better than OLS for power, however, ordinary least squares delivers better point estimates. Both generalized method of moments procedures exhibit lower power and more bias in estimates, supporting the argument that GMM does exhibit small sample bias. While all methodologies demonstrate capabilities in rejecting a false null hypothesis, all methods, in turn, also tend to overreject a true null hypothesis. This indicates that discretion and economic theory must be utilized in the discovery of asset-pricing risk factors.

Chapter 5 provides the concluding remarks of this analysis on political risk and the pricing of securities. It also provides directions for future research. Supporting chapters including the references and appendices can be found sequentially.

Chapter 2

Estimating the Market Price of Terrorism Risk

2.1 Introduction

Recent testimony at the trial for Adis Medunjanin, a suspected al-Qaeda recruit who is thought to be responsible for the attempted bombing of the New York subway system in 2009, revealed that the Manhattan subway was not the original target of the terror plot (Stringer (2012)). According to the Wall Street Journal, one of the possible targets included the New York Stock Exchange. It is no surprise that one of the many targets of the al-Qaeda terror plot consisted of one of America's most important financial and economic symbols, the NYSE. It is well-known that terrorist organizations such as al-Qaeda, the Irish Republican Army, and the Popular Front for the Liberation of Palestine, amongst many others, are driven by perceived economic, political, and social injustices in an effort to discourage future globalization and the economic prosperity of other countries (see GTD (2011) and Malhorta (2008)).

The connection between terrorism and economic, political, and social unrest is a topic of much interest in the time since the September 11, 2001 terror attacks on the World Trade Center and the Pentagon, another al-Qaeda terror plot. Unfortunately, little research focuses on the economic determinants, or the economic conditions and factors, that contribute to the incidence of terrorism (see Abadie (2006), Blomberg, Hess, and Weerapana (2004), Piazza (2006), and Tavares (2004)). But the research that does exist indicates that there is a significant relationship between economic factors (such as country income, unemployment, and economic growth), social factors (such as population, income disparity, and political freedom), and the number of terrorist events worldwide. These results imply that terrorist activity is indicative of larger problems with the economic and political fundamentals. While we typically think of terrorist regimes as extremists, far-removed from the mainstream political mindset, if terrorism is instead representative of a general, underlying political sentiment, then terrorist activity can be seen as the beginning of a shift in political preferences and the consequent economic policies. In this context, terrorism can be viewed as a type of political uncertainty because terror activities have an unknown and unpredictable effect on political, and subsequently economic, outcomes. It is with this reasoning that I examine terrorism risk.

I hypothesize that terrorism risk, as a proxy for underlying political risk, is priced and I discover that this price is significant and positive. This investigation discovers the terrorism risk premium by using a linear factor asset pricing model and a terrorism risk index based on the number of monthly domestic terror events within the United States. I find that terrorism risk is positively priced for nonindustry returns between January 1971 and December 2010. Results, however, are inconsistent when the data is separated into time periods before and after September 11, 2001. This would suggest that the number of terrorist attacks may no longer be a concern in the American financial markets.

Since I am utilizing terror events as representative of underlying economic risk from a shift in fundamentals, it would be remiss not to further analyze those economic factors that contribute to terror. Perhaps if we discover the macroeconomic factors that contribute to terror activity, we can hedge terrorism risk by incorporating those variables as additional factors in asset pricing. In the final part of this investigation, I analyze the determinants of terror attacks using Hausman Taylor analysis, a panel estimation technique. There is some debate as to the effect of country income, political rights, and the level of democracy of a country on terrorist activity (see Abadie (2006), Blomberg, Hess, and Weerapana(2004), Kis-Katos, Liebert, and Schulze (2011)). In an effort to reconcile these disagreements, I hypothesize that all three of these variables have a negative effect on the number of terror attacks. I further hypothesize that income disparities contribute to terrorism, with a larger disparity having a larger effect. Using data provided by the START program out of the University of Maryland, I perform analysis on a time series of country-level terrorist events spanning eighteen years and 148 countries (GTD (2011)). I show that income has no effect on the amount of country-level terrorist activity and a decrease in civil liberties increases terror.

2.2 Related Literature

Most research into terror and the economy exists on the economic consequences of terror attacks. Previous inquiries indicate that terrorism has significant, albeit short-run consequences for the macroeconomy, industry, and the financial sector. Blomberg, Hess, and Orphanides (2004) determine that terror has a small and less persistent negative effect on growth. They further find a redirection of spending away from investment and towards government expenditures. Tavares (2004) analyzes both the costs of terrorism and the determinants. Tavares supports the findings of Blomberg et. al. (2004) by ascertaining that output costs are smaller in a democracy. Llussá and Tavares (2011) suggest that GDP is affected through private consumption and investment. Abadie and Gardeazabal (2008) further discover the terrorism affects the movement of capital across the country and subsequently affects GDP through investment. Berrebi and Klor (2010) focus their analysis on the defense industry, but they uncover a negative impact not only on defense-related companies but nondefense-related companies as well.

While there is some evidence to suggest that terrorism affects investment, previous analyses on terrorism and the financial markets largely focuses on stock prices and volatilities. Arin, Ciferri, and Spagnolo (2008) find a significant impact of terror on the markets. This is supported by Chesney, Reshetar, and Karaman (2011), who discover an effect in the stocks, bonds, and commodities markets. Karolyi and Martell (2006) report a drop in stock prices on the day of a terror event. Levy and Galili (2006) further analyze the effect of terrorism on daily trade volume but from the perspective of emotion and fear. Melnick and Eldor (2010) and Drakos (2010) also address investor fear and sentiment and analyze its effect on the stock exchange.

Due to the overwhelming significance of the September 11, 2001 terror attacks, much analyses exists on the financial implications. Charles and Darné (2006) examine the effect of the September 11th attacks on international stock markets discovering large shocks both temporary and permanent. In terms of risk, Choudry (2005) looks at the effect of September 11th on the time-varying betas of U.S. companies finding most companies affected, supporting the findings of Berrebi and Klor (2010). Terror attack risk is a source of much concern for industries and possible hedging strategies are investigated in Gulley and Sultan (2006) and Karloyi (2007) with mixed results.

The terrorism risk premium, on the other hand, has never been directly measured by way of linear factor model estimation. This endeavor is the first exercise to assess terrorism risk and its effect on asset pricing. This research is significant because if terrorism is indeed representative of underlying political discontent and the related risk is significant, then it can be used as a proxy for political risk. It is from this perspective that I analyze terrorism.

2.3 Data

2.3.1 Terror Events

I obtain data on terrorist events within the United States from the Global Terrorism Database (GTD (2011)). Sponsored by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) out of the University of Maryland, the Global Terrorism Database is the largest, open-source database cataloguing worldwide terrorist events from January 1970 through December 2010. The GTD contains information on more than 98,000 domestic, international and transnational events in over 200 countries. Each event contains between 45-120 variables of incident information such as date, attack type, location, target information, and much more. For the financial analysis of this endeavor, I focus on those events that occurred within the borders of the United States between 1971 and 2010 (I exclude 1970 as this year demonstrates a significant number of terrorist events, not only within the United States but around the world, and is thus a major outlier). For the estimation of the determinants, I use those events that occurred domestically for 148 countries from 1990-2008.

A shortcoming of the GTD is the lack of a single definition of terrorism. While the database does maintain several variables on inclusion criteria, which was formulated by the GTD advisory board, the final decision to include an incident is made by GTD supervisory staff and management using the aforementioned guidelines. Due to the difficult nature of determining a universally acceptable definition of terrorism, and in an effort to be as inclusive as possible, the encoded events span a range of definitions and leave it to the researcher to decide which events to utilize in their research. It should be noted, however, that the GTD does not include information on foiled or failed terror plots, threats, or state-sponsored terrorism. This is unfortunate, as investment is very much affected by perception and fear which can result from attempted or planned terror attacks. And state-sponsored terror can further lead to a change in economic principles, directly affecting political risk.

For the purposes of this investigation, it is not necessary to employ a formal definition of terrorism. The inclusion criteria utilized by the GTD advisory board is sufficient and though the following inclusion criteria does not need to be fully met to be included in this research, it does allude to the type of events catalogued in the database:

Criterion I: The act must be aimed at attaining a political, economic, religious, or social goal,

Criterion II: There must be evidence of an intention to coerce, intimidate, or convey some other message to a larger audience (or audiences) than the immediate victims,

Criterion III: The action must be outside the context of legitimate warfare activities.

From this information, I create a simple count variable, which I refer to as the terrorism index. Each event that satisfies any of the above criterion are coded as ‘1’ and ‘0’ otherwise. The events are then summed over the course of a month, creating a monthly time series of attacks that occurred within the United States between 1971 and 2010. I then portion the data into two subgroups: the time before September 11, 2001 and the time after. Neither group includes the month of September 2001 as the events of 9/11 alone marked a major turning point in U.S. history in terms of terror awareness and event significance and is thus an outlier.

2.3.2 Returns and Factors

2.3.2.1 30 Industry Portfolios and 100 Portfolios

I obtain portfolios from Kenneth R. French's data library (French (2012)). I use both the 30 industry portfolios and the 100 portfolios formed on size and book-to-market value. The firms used to calculate the 30 industry portfolios are taken from the NYSE, AMEX, and NASDAQ. Each firm is assigned to a particular industry portfolio at the end of June based on its SIC code at that time. The 100 portfolios are sorted based on the intersections of ten portfolios formed on size and ten portfolios formed on the ratio of book-equity to market-equity.

2.3.2.2 Fama-French Factors

In the seminal paper by Fama and French (1993), it was shown that the cross-section of average stock returns, and subsequently a large portion of systematic risk, can be explained by three common risk factors: an overall market factor, a factor related to firm size, and a factor related to firm book-to-market value. The market factor is calculated as the excess market return, or the value-weighted return on all NYSE, AMEX, and NASDAQ stocks minus the one-month Treasury bill rate. The firm factors are both calculated using six portfolios sorted based on size and book-to-market value and are meant to mimic those risk factors using portfolio returns. Size is calculated as the stock price times the number of shares. The portfolio is created based on the monthly difference between the average returns of the small-stock portfolios and the average returns of the big-stock portfolios (Small-Big). The book-to-market portfolio is calculated similarly by first computing the ratio of the book value of the firm's stock to its market value. The portfolio is based on the difference between the average returns of the value portfolios minus the average returns of the growth portfolios (High-Low). The Fama-French factors are also obtained from Kenneth R. French's website (French (2012)).

2.4 Methodology

Consider the basic pricing formula, $p_t = E[m_{t+1}x_{t+1}]$ or equivalently $1 = E[m_{t+1}, R_{t+1}]$ where $R_{t+1} = \frac{x_{t+1}}{p_t}$ are gross returns on assets (Cochrane (2005)). Asset pricing models usually only differ in their interpretation of the stochastic discount factor, m_{t+1}. An important class of asset pricing models is the linear factor model, or the linear beta pricing model, which interprets the stochastic discount factor as a linear combination of various pervasive risk factors in the form of $m = b_0 - f'b_1$ (in this example, I use a single factor and I eliminate the time subscripts for simplicity). It can be shown that the linear beta restriction is equivalent to the linear stochastic discount factor assumption (Cochrane (2005)). Excess returns can also be used in place of gross returns to simplify analysis, but the use of excess returns requires slightly different initial assumptions: $m = 1 - b(f - E[f])$ (see Chapter 4 for further details). To test whether terrorism risk accounts for the variation in the cross section of asset returns, I utilize excess returns in standard linear factor asset pricing models.

Denote by R_t a vector of returns in excess of the risk free rate on N assets at time t and f_t as the vector of K economy-wide factors at time t. Now assume that returns follow the linear process

$$R_{i,t} = \alpha_i + f_t'\beta_i + u_{i,t}, \quad i = 1, \dots, N, \quad t = 1, \dots, T \tag{2.1}$$

where the errors $u_{i,t}$ are uncorrelated with the factors for all i with mean zero and β_i is the vector of betas, or factor loadings, for asset i which is given by

$$\beta_i = E[(f_t - E[f_t])(f_t - E[f_t])']^{-1} E[(R_{i,t} - E[R_{i,t}])(f_t - E[f_t])], \tag{2.2a}$$

$$\Sigma_R = E[(R_{i,t} - E[R_{i,t}])(R_{i,t} - E[R_{i,t}])'], \tag{2.2b}$$

$$\Sigma_f = E[(f_t - E[f_t])(f_t - E[f_t])']. \tag{2.2c}$$

Under these assumptions, the linear beta pricing model places the restriction

$$E[R_{i,t}] = a_0 + \lambda' \beta_i, \quad i = 1, \ldots, N \tag{2.3}$$

where λ is the vector of risk premia and a_0 is a vector of constants (see Jagannathan, Schaumburg, and Zhou (2010)). Another way to interpret the two equations above is to consider the factor loadings, β_i, as the relationship between the risk factors, f_t, and the returns, R_t. Then λ can be interpreted as the price of risk or the amount of compensation that investors require for holding onto assets with the risk factors present. If λ is positive and significant, then we would say that the factor is priced because it does explain the variation in the cross section of asset prices.

Classic articles by Chen, Roll, and Ross (1986) and Fama and French (1993) use linear factor models to explain the cross sections of assets, each with their own risk factors. While Chen, Roll, and Ross (1986) use macroeconomic variables in their analysis, Fama and French create mimicking portfolios that capture the pervasive risks presented by firm characteristics such as firm size and book-to-market effects. Along with these two factors, Fama and French also use the market portfolio in excess of the risk-free rate to create the Fama-French factors which are now commonly used in empirical studies as they do indeed account for much of the variation in the cross section of security returns.

2.4.1 Cross-Sectional Regression

There are several methods to evaluate linear factor models, two of which I employ in this empirical investigation (I follow the notation of Jagannathan, Skoulakis, and Wang (2010)). The first is the simplest and most robust, cross-sectional regression which I also use in Chapter 3. Cross-sectional regression estimation is based on the Fama-MacBeth technique developed in Fama and MacBeth (1973) to assess the relationship between expected returns and factor betas (Jagannathan, Skoulakis, and Wang (2010)). It is performed in two passes, which is why it is generally referred to as “two-pass regression". The first pass is a time series regression to estimate the relationship between the returns and the factor loadings (betas). The second is a cross sectional regression to measure the relationship between the factor loadings and average returns.

Consider the following reinterpretation of the beta representation,

$$E[R_t] = a_0 1_N + B\lambda = Xc \tag{2.4}$$

where

$$X = [1_N \quad B], \quad c = [a_0 \quad \lambda']', \tag{2.5}$$

X is a N x $(K+1)$ matrix and c is a $(K+1)$ vector of risk premia. Then standard OLS estimation of c yields

$$c = (X'X)^{-1}X'E[R_t]. \tag{2.6}$$

Two-pass regression is essentially the same estimation technique as Fama-MacBeth estimation, only in a slightly different form. Unlike Fama-MacBeth, which estimates a separate risk premium $\hat{c}_t$ over the full cross section at each time period in the second pass and then averages over all estimates, cross-sectional regression estimates a single $\hat{c}$ over the full time series using an average of the returns for each cross section. Both forms yield identical results for $\hat{c}$ and $Var(\hat{c})$ making them equivalent and interchangeable estimation methods (Kleibergen (2009) and Jagannathan, Skoulakis, and Wang (2010)).

Regression can be performed either with or without the constant a_0. Per theory, this vector should equal the zero-vector. If regression is run allowing for estimation of the constant, then the parameter can be tested for significance (Cochrane (2005)). If the model is correctly specified, then $a_0 = 0_N$ (Jagannathan, Schaumburg, and Zhou (2010)). Most researchers prefer to estimate the constant along with the other parameters as a test of model validity.

We can further work backwards from the definition of B and write the time series regression as

$$R_t = E[R_t] + B(f_t - E[f_t]) + u_t \tag{2.7}$$

where u_t has mean zero and is uncorrelated with the factors. If we substitute for the expected returns the beta pricing restriction, then we derive the return process

$$R_t = a_0 1_N + B(f_t - E[f_t] + \lambda) + u_t \tag{2.8}$$

Of course, two-pass estimation is robust and easy to apply in large samples, however it does impose assumptions that are not overly realistic and, the larger problem, the second pass estimation requires the use of an estimated regressor causing the classic error-in-the-variables problem. The standard assumptions for this estimation process include conditional homoskedasticity, which holds when the returns and factors are identical and independently normally distributed (Jagannathan, Schaumburg, and Zhou (2010)). This is a nice assumption because standard t-tests can then be calculated to test the validity of the relevant coefficients. But there is some empirical evidence to indicate that returns are actually heteroskedastic, nonnormally distributed, and even autocorrelated.

The error-in-the-variables problem is also not one that can be overlooked. There are several prescribed methods for compensating for this problem. One method is to use portfolios instead of individual stocks as the testing assets. It is believed that the large number of stocks employed are estimated precisely enough to compensate for the error. Another method, suggested by Fama and Macbeth (1973), is to estimate a separate variance matrix accounting for the error in the second stage, however, this method has proven to overstate the precision of estimates and is subsequently inefficient under the assumption of conditional homoskedasticity. And yet another method is to use generalized least squares in the second pass of estimation. c is then formed as

$$c = (X'QX)^{-1}X'QE[R_t] \tag{2.9}$$

where Q is positive definite N x N matrix. With this method, portfolio formation may not even be necessary. This is the method I utilize to account for the error-in-the-variables problem in the empirical section.

2.4.2 Generalized Method of Moments Estimation

The assumptions and problems posed by the cross-sectional regression method make some researchers uncomfortable. So I also examine the cross section of returns using generalized method of moments estimation. This technique is appealing to use under more realistic assumptions because it allows for serial correlation and conditional heteroskedasticity (see Jagannathan, Skoulakis, and Wang (2010)). However, GMM is the most efficient unbiased estimator when returns and factors are homoskedastic and independent.

The generalized method of moments is further advantageous because it allows estimations of all model parameters in a single pass, eliminating the earlier error-in-the-variables problem. But it should be noted that GMM has been known to overreject models with small sample size and time series compared to other methods of estimation (more on this in Chapter 4). GMM can be performed using either the linear beta pricing model representation or the earlier stochastic discount factor representation. Both are asymptotically equivalent, so for comparison, I will estimate the empirical model using the linear factor representation.

Remember the return process generated in the previous section, ignoring the constant for the time being:

$$R_t = B(f_t - E[f_t] + \lambda) + u_t \tag{2.10}$$

where B is the vector of factor loadings, $B = E[R_t, (f_t - E[f_t])]Var[f_t]^{-1}$. Also remember the properties of u_t

$$E[u_t] = 0_N \tag{2.11a}$$

$$E[u_t f_t'] = 0_{NxK} \tag{2.11b}$$

From the above equations the moment restrictions are then

$$E[R_t - B(f_t - E[f_t] + \lambda)] = 0_N \tag{2.12a}$$

$$E[[R_t - B(f_t - E[f_t] + \lambda)]f_t'] = 0_{NxK} \tag{2.12b}$$

$$E[f_t - E[f_t]] = 0_K \tag{2.12c}$$

The last equation identifies the risk premium λ. These three equations combine to formulate the expected value of the moment restriction, or more precisely $E[g(x_t, \theta_0)] = 0_N$ where $\theta = [\delta' \; vec(B)' \; \mu']'$. We then use the sample analogue $g_T(\theta) = \frac{1}{T}\Sigma_{t=1}^{T} g(x_t, \theta)$ to solve

$$\min_{\theta} g_T(\theta)' S_T^{-1} g_T(\theta), \tag{2.13}$$

where S_T is the consistent estimator of the spectral density matrix of $g(x_t, \theta)$, and find the GMM estimator $\hat{\theta}$.

To test the model's validity, I compute the J-statistic

$$J_T = T g_T(\hat{\theta}_T)' S_T^{-1} g_T(\hat{\theta}_T) \quad \xrightarrow{D} \quad \chi^2(N-K) \quad as \quad T \to \infty, \tag{2.14}$$

which is χ^2 in asymptotic distribution. In most applications, GMM is performed either in two stages or iteratively, the difference being the number of times the weighting matrix is reestimated. For this analysis, I employ two-step GMM for its simplicity.

2.5 Empirical Results

2.5.1 Summary Statistics

Looking at the summary statistics in Table 2.1, it is apparent that a sizable share of terrorist events occurred before September 11, 2001. For a period of 368 months, not including the year 1970, the total number of terror events before 9/11 is 1739, out of a possible 2359 for the entire time period of 492 months. The average number of monthly events before 9/11 are not too different from the total average at 4.73 and 4.79, respectively. Standard deviation is also similar at 5 events before September 11th and 7.59 for the total time period.

The time period after September 11, 2001, however, maintains noticeably different results. The duration of 111 months is not even half the size of the time period before 9/11, not including the month of September 2011. The shorter time series also yields a smaller number of events at 156 with a smaller average number of monthly events at 1.41 and standard deviation of 2.47 events. These markedly different results for the time period subsets comes as little surprise as the occurrence of the September 11th terror attacks is not the median event of the total time series.

Notice that the maximum number of monthly events for the total time series is 65, while the maximum number of events for the time periods before and after September 11th are 38 and 20, respectively. Indeed, April 1970 saw the most terrorism at 65 events with other months of 1970 experiencing numbers as high as 62, 55, and 49 events. For this reason, I eliminate the year 1970 from the period before 9/11.

Table 2.1: **Summary Statistics for the Terrorism Index**

Terrorism Index Date Range	*Full Time Series* Jan 1971-Dec 2010	*Before Sept 11, 2001* Jan 1971-Aug 2001	*After Sept 11, 2001* Oct 2001-Dec 2010
Period (Months)	492	368	111
Total Events	2359	1739	156
Mean	4.795	4.726	1.405
Standard Dev	7.594	5.001	2.473
Minimum	0	0	0
Maximum	65	38	20

2.5.2 Cross-Sectional Regression

Two-pass least squares regression yields incongruent results for the 30 industry portfolios and 100 portfolios. For the 30 industry portfolios, the terrorism index is not priced, save for the time after September 11, 2001 where it maintains mild significance in the presence of the Fama-French factors (see Table 2.2). Interestingly, in all time periods, the constant is only three times statistically no different from zero. In the time after September 11th, the second scenario, which includes only the terrorism index and the market return, performs the best with both factors maintaining significance and the constant invalid. But the results for the analysis for the full time series should reflect the results of the subset if they are valid, which it does not. Although the terrorism index does not do well to explain the cross section of the industry portfolios, neither do the Fama-French factors.

Unlike the 30 industry portfolios, for the 100 portfolios the terrorism index factor for the total time period and the time before 9/11 is significant and positive. Results for the 100 portfolios in Table 2.3 are consistent with the expectation that terrorism risk is significantly priced, although that price is surprisingly high. The market factor performs well when combined with the size factor, however, the book-to-market equity factor only performs well when the market factor is excluded from the model. The constant term is also significantly different from zero in all three time periods.

For the total time period, the terrorism risk premium is considerably larger than the premia for the other factors. This is also true for the time period before September 11th, although this risk premium is just slightly larger than for the full time series. The lack of terrorist events since that fateful day might explain the smaller risk premium. The risk premium further decreases when the other factors are included in the model. After 9/11, risk premium is not much larger than zero, but much more in line with the other factors. This result implies that investors now require less return for holding onto risky portfolios. Notice also that in the fourth scenario the terrorism index is priced in the presence of the Fama-French factors.

Table 2.2: **Risk Premia(λ_i) Results Using Cross-Sectional Regression Estimation–** ***30 Industry Portfolios***

Time Period	Terrorism Index	Market	Small-Big	High-Low	Constant
Jan 1971-Dec 2010	0.655				0.581***
	(0.85)				(18.24)
	0.838	-0.09			0.669***
	(1.02)	(-0.62)			(4.60)
	0.749		-0.085	-0.002	0.619***
	(0.87)		(-0.81)	(-0.01)	(11.59)
	0.536	0.171	-0.187	0.003	0.98**
	(0.55)	(0.48)	(-0.79)	(0.03)	(1.93)
Jan 1971-Aug 2001	0.086				0.578***
(Before 9/11/01)	(0.12)				(16.09)
	0.278	-0.079			0.651***
	(0.34)	(-0.44)			(3.87)
	0.09		-0.331***	-0.221**	0.599***
	(0.13)		(-2.77)	(-1.98)	(11.92)
	-0.395	0.412	-0.49***	-0.142	0.304
	(-0.52)	(1.29)	(-2.90)	(-1.13)	(1.30)
Oct 2001-Dec 2010	1.323*				0.755***
(After 9/11/01)	(1.79)				(7.99)
	1.443**	0.617**			0.093
	(2.14)	(2.50)			(0.33)
	1.534*		0.343	0.096	0.423**
	(1.83)		(1.55)	(0.31)	(2.24)
	1.57*	0.679	-0.084	0.079	0.05
	(1.92)	(1.33)	(-0.22)	(0.26)	(0.15)

Two-pass regression using monthly excess returns: OLS first pass, GLS second pass. z-statistics are reported in parenthesis below regression estimates. ***significance at the 1% level, **significance at the 5% level, *significance at the 10% level. Terrorism index calculated using data obtained from the Global Terrorism Database. 30 industry portfolios and Fama-French factors obtained from Kenneth R. French's website.

Table 2.3: **Risk Premia(λ_i) Results Using Cross-Sectional Regression Estimation–** ***100 Portfolios***

Time Period	Terrorism Index	Market	Small-Big	High-Low	Constant
Jan 1971-Dec 2010	6.017***				0.579***
	(17.57)				(10.50)
	6.293***	-1.507***			2.186***
	(19.90)	(-4.65)			(6.25)
	5.702***		0.458***	0.739***	0.435***
	(17.80)		(3.88)	(5.96)	(4.35)
	5.609***	-2.67***	0.78***	0.198	2.817***
	(19.79)	(-5.31)	(6.47)	(1.33)	(6.16)
Jan 1971-Aug 2001	7.336***				0.467***
(Before 9/11/01)	(14.05)				(5.73)
	7.784***	-1.889***			2.424***
	(16.05)	(-4.57)			(5.57)
	6.735***		0.766***	1.027***	0.434***
	(13.47)		(4.30)	(5.56)	(3.30)
	6.842***	-4.004***	0.969***	-0.171	3.773***
	(15.26)	(-4.97)	(5.89)	(-0.58)	(5.53)
Oct 2001-Dec 2010	0.142				0.781***
(After 9/11/01)	(0.49)				(21.39)
	0.108	0.293			0.446*
	(0.37)	(1.42)			(1.87)
	0.323		0.319***	0.229***	0.24**
	(1.28)		(4.25)	(2.85)	(2.49)
	0.533**	-0.92***	0.54***	0.321***	0.959***
	(2.21)	(-3.91)	(6.00)	(4.09)	(4.68)

Two-pass regression using monthly excess returns: OLS first pass, GLS second pass. z-statistics are reported in parenthesis below OLS regression estimates. ***significance at the 1% level, **significance at the 5% level, *significance at the 10% level. Terrorism index calculated using data obtained from the Global Terrorism Database. 100 portfolios and Fama-French factors obtained from Kenneth R. French's website.

2.5.3 Generalized Method of Moments Estimation

The results from two stage generalized method of moments estimation are not too dissimilar numerically from the results of the cross-sectional regression. For the 30 industry portfolios, the terrorism index is unpriced throughout. This conflicts with the previous research by Choudry (2005) and Berrebi and Klor (2010) who discover the effects of terrorism reflected in industry returns.

Interestingly, the model performs well in the time period since 9/11, but only when the market factor is the only factor present. Constants are mostly different from zero.

Table 2.4: **Risk Premia(λ_i) Results Using Generalized Method of Moments Estimation–** ***30 Industry Portfolios***

Time Period	Terrorism Index	Market	Small-Big	High-Low	Const	J-Statistic
Jan 1971-Dec 2010	0.367				0.577***	0.765 (p = 0.682)
	(0.96)				(0.035)	
	0.408	-0.010			0.672***	1.445 (p = 0.836)
	(0.819)	(0.123)			(0.142)	
	0.656		-0.069	-0.033	0.571***	3.98 (p = 0.679)
	(0.896)		(0.082)	(0.087)	(0.051)	
	0.031	0.157	-0.172	-0.05	0.472***	3.835 (p = 0.872)
	(1.007)	(0.24)	(0.18)	(0.081)	(0.165)	
Jan 1971-Aug 2001	-0.058				0.59***	1.797 (p = 0.407)
(Before 9/11/01)	(0.63)				(0.039)	
	-0.059	-0.076			0.672***	4.021 (p = 0.403)
	(0.628)	(0.17)			(0.165)	
	0.031		-0.333***	-0.226**	0.607***	4.527 (p = 0.606)
	(0.551)		(0.102)	(0.095)	(0.046)	
	-0.555	0.308	-0.411***	-0.174*	0.372**	6.056 (p = 0.641)
	(0.60)	(0.231)	(0.143)	(0.092)	(0.162)	
Oct 2001-Dec 2010	0.553				0.732***	0.881 (p = 0.644)
(After 9/11/01)	(0.687)				(0.094)	
	0.794	0.477***			0.292	2.67 (p = 0.615)
	(0.64)	(0.166)			(0.183)	
	0.675		0.309*	-0.019	0.465***	1.289 (p = 0.972)
	(0.717)		(0.185)	(0.234)	(0.146)	
	0.876	0.608**	-0.187	0.192	0.187	4.731 (p = 0.786)
	(0.647)	(0.288)	(0.27)	(0.251)	(0.162)	

Standard errors are reported in parenthesis below GMM regression estimates. ***significance at the 1% level, **significance at the 5% level, *significance at the 10% level. Terrorism index calculated using data obtained from the Global Terrorism Database. 30 industry portfolios and Fama-French factors obtained from Kenneth R. French's website.

For the 100 portfolios, GMM estimation prices terrorism positively throughout the full time series and before 9/11. But notice that for the time period after September 11th, the terrorism index premium is significantly priced when the Fama-French factors are also present. This is consistent with the cross-sectional regression results. Perhaps this is indicative of a small amount of political risk in the time since 9/11. Consistent with those results, too, the terrorism risk premium is also surprisingly large relative to the other premia. The J-statistic is calculated to assess each individual model's validity. The null hypothesis for the J-statistic, that the model is correctly specified and the GMM is small, is rejected throughout for both sets of portfolios.

Table 2.5: **Risk Premia(λ_i) Results Using Generalized Method of Moments Estimation–** ***100 Portfolios***

Time Period	Terrorism Index	Market	Small-Big	High-Low	Const	J-Statistic
Jan 1971-Dec 2010	5.315***				0.604***	1.733 (p = 0.421)
	(1.002)				(0.046)	
	5.251***	-1.299***			1.987***	3.37 (p = 0.498)
	(0.946)	(0.314)			(0.319)	
	4.997***		0.448***	0.758***	0.469***	5.758 (p = 0.451)
	(1.121)		(0.147)	(0.176)	(0.101)	
	5.639***	-1.474*	0.633***	0.481***	1.759***	6.525 (p = 0.589)
	(0.644)	(0.796)	(0.205)	(0.139)	(0.643)	
Jan 1971-Aug 2001	5.99***				0.535***	1.842 (p = 0.398)
(Before 9/11/01)	(1.849)				(0.061)	
	5.741***	-1.499***			2.09***	2.935 (p = 0.569)
	(1.671)	(0.297)			(0.279)	
	5.489***		0.635**	1.007***	0.578***	4.471 (p = 0.613)
	(1.995)		(0.281)	(0.323)	(0.115)	
	6.635***	-1.459	0.714**	0.549	1.74	4.975 (p = 0.76)
	(1.332)	(1.37)	(0.288)	(0.488)	(1.073)	
Oct 2001-Dec 2010	0.185				0.783***	0.137 (p = 0.934)
(After 9/11/01)	(0.355)				(0.036)	
	0.202	0.309			0.43*	0.615 (p = 0.961)
	(0.33)	(0.217)			(0.257)	
	0.419		0.275***	0.246***	0.294***	3.915 (p = 0.688)
	(0.295)		(0.091	(0.095)	(0.114)	
	0.616**	-0.899***	0.492***	0.333***	0.995***	4.027 (p = 0.855)
	(0.308)	(0.261)	(0.101)	(0.083)	(0.237)	

Standard errors are reported in parenthesis below GMM regression estimates. ***significance at the 1% level, **significance at the 5% level, *significance at the 10% level. Terrorism index calculated using data obtained from the Global Terrorism Database. 100 portfolios and Fama-French factors obtained from Kenneth R. French's website.

The inconsistent results between the portfolios is intriguing. It is possible that industry portfolios are not as affected by terrorism risk as those organized based on size and book-to-market equity? Since we are analyzing terror as a type of political uncertainty, its affect on portfolios should be systematic. It is also possible that the smaller set of testing portfolios suffers from the small sample bias of the second method of estimation, GMM. This dilemma provides the motivation for Chapter 4. But without a more persuasive argument, there is nothing more than an inconclusive result for the data segregation.

2.6 The Determinants of Terrorism

In this section I analyze the effects of macroeconomic variables on the act of terror. The discovery of relevant economic and social variables on the incidence of terrorism compounds the argument that terrorism is indicative of a deeper shift in the economic fundamentals and thus a source of political uncertainty. And perhaps the inclusion of such relevant variables in asset pricing models can mitigate future risk.

Previous research on the determinants of terrorism, or what makes a country more susceptible to experience a terror attack, has been limited mostly due to a lack of quality data and estimation techniques. In Tavares (2004), not only are the effects of terrorism analyzed, but Tavares also discovers that richer countries are more likely to suffer from terror attacks, although democracies are less likely. Abadie (2006) disagrees, noting that richer countries are no more likely than poorer countries to experience a terror attack if they maintain the same level of civil liberties and democracy. Both empirical analyses utilize ordinary least squares regression, but Piazza (2006) supports the findings of Abadie (2006) using the multiple regression technique. Piazza further suggests that social variables have much more influence on terrorism than economic variables.

To account for the relative differences in the effect of country level income on terrorist activity, Blomberg, Hess, and Weerapana (2004) and Blomberg and Hess (2008a) split the data into subcategories: high income and low income countries. The results are markedly different for each group, with per capita income increasing the incidence of terrorism for the higher income countries and lowering it for lower income countries. (Blomberg, Hess, and Weerapana (2004) use a markov process in their investigation whereas Blomberg and Hess (2008a) use a panel estimation technique).

The most recent empirical investigations into the determinants of terror events rely on panel estimation techniques. Using negative binomial fixed effects regression, Caruso and Schneider

(2011) determine that social welfare variables, specifically those related to current economic opportunities, lower the incidence of terrorism, although real GDP is positively associated with terrorist brutality. Kis-Katos, Liebert, and Schulze (2011) also use negative binomial fixed effects regression and they determine that terror increases with income and democracy.

In an effort to reconcile the various disagreements on the effect of country income, political rights, and the level of democracy of a country, I focus on these variables hypothesizing that all three have a negative effect on the number of terror attacks. I further hypothesize that income disparity contributes positively to terror activity. Using data provided by the START program, I perform analysis on a time series of annual, country-level terrorist events spanning eighteen years and 148 countries. Since it is possible that a high amount of domestic terrorism influences gross domestic product, even in the short-run (see Tavares (2004), Abadie and Gardeazabal (2008), and Llussá and Tavares (2011)), I consider this variable endogenous in my analysis. Per the use of cross-sectional time series, an endogenous income variable, and time-invariant geographic variables, Hausman Taylor estimation is appropriate.

Surprisingly, I discover counterintuitive results. First, I show that wealth does not contribute to terrorist activity while country size and location do. Terrorism also decreases with population and education levels but increases with a decrease in civil liberties. This research differs from previous, particularly Caruso and Schneider (2011) and Kis-Katos, Liebert, and Schulze (2011), in the use of the Hausman Taylor panel estimation technique and the simultaneous incorporation of endogenous and geographic variables with a slightly different outcome.

2.6.1 Explanatory Variables

Many of the explanatory variables are obtained from the World Bank website (WDI (2012)). To understand the effect of country income on the number of terror events, I utilize GDP per capita (in current US dollars). High inflation and unemployment is often associated with higher crime rates and has previously been shown to be positively associated with terrorist events (see Goldstein (2006), Piazza (2006), and Caruso and Schneider (2011)). So I include total unemployment (as a percentage of the total labor force) and the GDP deflator as a measure of inflation (annual percentage).

To expand further on the effect of income on terrorism, I hypothesize that income distribution influences terror activity. I test if disproportionate income distribution and relative poverty have a significant effect on the number of terror events by using the Gini coefficient. The Gini coefficient measures the extent of the distribution of wealth using an index ranging from 0 to 100. A Gini index of '0' represents perfect equality but an index of '100' is perfect inequality. Other social variables include population (total), general education level (gross percentage of age-appropriate enrolled in secondary education), and a measure of civil liberties (see Krueger and Malečková (2003) for details on the contribution of education).

Previous literature suggests that the amount of civil liberties, and the subsequent response of government to the desires of the constituents, contributes to the incidence of terrorism (see Abadie (2006), Piazza (2006), Blomberg and Hess (2008a), Kis-Katos et al (2011), and Caruso and Schneider (2011)). Variables that account for political rights and the level of democracy are often utilized, though controversial in their abilities to accurately measure freedom and government interaction. I choose to utilize the civil liberties index from Freedom House as the democracy variable in this analysis (PR (2011)). The index assigns a value from 1 to 7 with the lower end of the scale representing the highest degree of freedom (for example, the United States scores a 1 throughout).

The final set of independent variables are geographic. Abadie (2006) and Blomberg and Hess (2008a) suggest that the location of a country contributes to terrorist activity, with the more isolated countries experiencing less terrorism. I employ the same geographic variables utilized by Abadie (2006), which were obtained from John Luke Gallup's website (Gallup, Mellinger, and Sachs (1999) and Gallup (2011)). The geographic variables include country land area (km^2), mean elevation (meters above sea level), and mean distance to the nearest coastline or sea-navigable river (km).

It has been suggested that the use of social variables that account for ethnic, linguistic, and religious differences be utilized in the estimation on the determinants of terror (Piazza (2006) and Burgoon (2011)). However, there does not exist a single diversity index that is without controversy. Property rights and law enforcement has also historically contributed to terrorism on an international level (De Soto (1989)). But property rights is another controversial variable that is not regularly utilized in macroeconomic or panel investigations. Further this endeavor is, primarily, a look at terrorism as a market risk factor. The search for the economic determinants of terror is simply an obvious extension of an analysis on the contributors to political risk. The search for a full list of determinants is a subject for future pursuits and not the original purpose of this chapter. So for this reason, I choose to relegate the determinants analysis to those socioeconomic variables already listed.

2.6.2 Methodology

Unlike standard time-series or cross-sectional datasets for which we can use ordinary least squares estimation, panel data consists of both N cross-sectional units with fewer time T observations. Consider the model

$$y_{it} = \alpha + x'_{it}\beta + u_{it}$$

where t denotes time, $t = 1,\ldots,T$, and i represents the cross-sectional units which can be firms, countries, etc, $i = 1,\ldots,N$ (Baltagi 2008). So x_{it} is the itth observation on K explanatory variables. The disturbances, u_{it}, maintain a one-way error component, $u_{it} = \mu_i + v_{it}$, where μ_i denotes the unobservable, individual specific trait that is time-invariant and v_{it} is the remainder disturbance. These individual effects are the reason we cannot use standard OLS regression in panel data-the individual effects act as separate intercept terms for each cross-sectional unit and simply eliminating this variable from the model will yield biased estimators, the result of running a regression with missing variables when the true model contains them.

2.6.2.1 Hausman Taylor Estimation

Fixed effects regression, generally considered the standard estimation technique for panel data analysis, assumes that there is no correlation between the explanatory variables and the individual effects. Hausman Taylor estimation, on the other hand, works under the assumption that some of the explanatory variables are endogenous while the rest are exogenous and splits the data as such.

Consider the model

$$y_{it} = \alpha + x_{it}'\beta + z_i'\gamma + \mu_i + v_{it}$$

where $i = 1,\ldots,N,\ t = 1,\ldots,T$, and z_i are cross-sectional, time-invariant parameters, like gender for example, that are separate from μ_i, which is more like individual talent. In matrix form,

$$y = X\beta + Z\gamma + Z_\mu\mu + v$$

where $X = (R_1 \vdots R_2),\ Z = (S_1 \vdots S_2)$. Hausman Taylor further assumes that R_1 and S_1 are exogenous or predetermined and R_2 and S_2 are endogenous, or $E[\mu|R_1,S_1] = 0,\ E[\mu|R_2,S_2] \neq 0$.

Now, since some of the variables are endogenous, we cannot use least squares estimation techniques without encountering problems of parameter consistency. So Hausman Taylor estimation works by using the instrumental variables technique. Here, we use the exogenous variables as instruments for the endogenous variables: R_1 and S_1 are instruments for themselves, while PR_1 is the instrument for S_2, where $P = Z_\mu(Z_\mu'Z_\mu)^{-1}Z_\mu'$, and QR_2 is the instrument for R_2, where Q is the residual maker. So the final instrument matrix is

$$[R_1 \vdots QR_2 \vdots S_1 \vdots PR_1].$$

2.6.3 Empirical Results

Using data on 148 countries from 1990-2008, I investigate the following model:

$$
\begin{aligned}
lnTerrorEvents_{it} = {} & \mu_i + \beta_1 lnGDPPC_{it} + \beta_2 GDPdefl_{it} + \beta_3 Unemp_{it} + \beta_4 lnPop_{it} + \beta_5 GINI_{it} + \\
& \beta_6 Education_{it} + \beta_7 CivLib_{it} + \beta_8 lnLandArea_i + \beta_9 lnElevation_i + \beta_{10} lnDistance_i + \\
& \nu_{it}
\end{aligned}
$$

where $i = 1, \ldots, 148$, $t = 1, \ldots, 19$ and

lnTerrorEvents = log number terror events	lnGDPPC = log GDP per capita
GDPdefl = GDP deflator/1000	Unemp = total unemployed(%)
lnPop = log total population	GINI = Gini coefficient(0-100)
Education = high school enrollment(%)	CivLib = civil liberties index(1-7)
lnLandArea = log land area	lnElevation = log elevation(mean)
lnDistance = log distance to waterway	

Once again, the only endogenous variable I utilize is the income variable, GDP per capita.

2.6.3.1 Summary Statistics

The summary statistics are reported in Table 2.6. The average annual number of terror events is 15.2 between 148 countries in 13 regions around the world (see Appendix A for further details on region and country-level statistics). But the data does maintain a large standard deviation at 59.5 events. Of course, the number of events can never be negative so the minimum number of events is 0. And the highest number of terror events in one year was 1104 which occurred in Iraq in 2005.

2.6.3.2 Hausman Taylor Estimation

In Table 2.7, you will find the results for Hausman Taylor estimation along with ordinary least squares regression and fixed effects estimation for comparison. The OLS regression results support those in Abadie (2006). Country level income has no statistically significant effect on terrorism, while some of the geographic variables do. Interestingly, both the Gini coefficient, which represents income disparity, and the civil liberties index do not contribute to terrorism. The constant term is also inexplicably negative representing a negative amount of terrorism on average for each country regardless of socioeconomic status.

Table 2.6: **Summary Statistics for the Terror Events Panel**

Time Period	1990:2008
Number of Regions	13
Number of Countries	148
Total Number of Events	42755
Mean Events per Year	15.204
Standard Deviation	59.479
Minimum	0
Maximum	1104

Fixed effects estimation confirms the OLS results regarding income and the Gini coefficient. But results that differ include the employment, population, and education variables. Unemployment and education both lose their affect on terrorist activity while a larger population experiences less terrorism. This outcome is rather counterintuitive. But notice the democracy variable–a decrease in civil liberties increases terror. Once again, on a scale from 1-7, 1 represents the highest level of liberty. The constant term is also quite large at 37.8 events. Fixed effects regression will not estimate parameters for time-invariant variables so there are no results to report for the geographic variables.

The final column in Table 2.7 contains the results of the Hausman Taylor estimation method. According to the Hausman Taylor results, country wealth does not contribute to terrorism, neither do employment rates nor income disparity. Similar to the fixed effects estimation, a larger population decreases the incidence of terrorism, as does education, with a slightly smaller effect for both. A decrease in civil liberties results in more terrorism. Notice also that both land area and the distance to nearest coastline or sea-navigable river are both significantly contributing variables. A larger country tends to experience more terrorism, but the further away from a major waterway the less terror. This suggests that landlock has a negative impact on terrorism. The Hausman model further indicates an insignificant constant term. This could mean that without these parameters present, the country is likely not to experience terrorism.

Table 2.7: **Parameter Estimates for the Determinants of Terrorism**

Variable	**Ordinary Least Squares Estimation**	**Fixed Effects Estimation**	**Hausman Taylor Estimation**
GDP Per Capita (Endogenous)	0.013 (0.31)	0.086 (0.85)	-0.094 (-1.06)
GDP Deflator	0.345*** (3.37)	0.206*** (2.54)	0.205*** (2.61)
Unemployment Rate	0.047*** (6.17)	-0.008 (-0.94)	-0.008 (-1.05)
Population	0.511*** (13.65)	-2.247*** (-6.21)	-0.691*** (-3.02)
Secondary Enrollment	-0.004*** (-3.38)	-0.002 (-1.35)	-0.002** (-1.97)
Gini Coefficient	-0.001 (-0.64)	-0.003 (-1.33)	-0.003 (-1.37)
Civil Liberties Index	0.055 (1.57)	0.349*** (6.37)	0.367*** (7.03)
Land Area	-0.151*** (-3.58)		0.878*** (2.81)
Elevation	0.194*** (3.81)		0.482 (1.1)
Distance to Waterway	-0.089 (-1.55)		-0.993** (-2.27)
Constant	-5.776*** (-10.03)	37.766*** (6.54)	3.465 (0.84)

t-statistics are reported in parenthesis below OLS and FE regression estimates. *z*-statistics are reported for HT regression estimates. ***significance at the 1% level, **significance at the 5% level, *significance at the 10% level. Terrorism data obtained from the Global Terrorism Database, civil liberties index obtained from Freedom House, and geographic variables obtained from John Luke Gallup's website. All other variables are obtained from World Bank.

To test the validity of the Hausman Taylor model, I use both the Breusch-Pagan test and the Hausman test. The Breusch-Pagan test in Table 2.8 indicates that panel estimation is preferred to ordinary least squares estimation. And the Hausman test further concludes that Hausman Taylor estimation is preferred to fixed effects regression.

Table 2.8: **Data Testing**

Test	**Statistic**	**P-Value**
Breusch-Pagan (Panel Data)	1567.96	0.000
Hausman (Fixed Effects vs Hausman Taylor)	33.88	0.000

2.7 Conclusion

It has been argued that terrorism is suggestive of alterations in the deeper economic fundamentals and thus representative of greater political risk, so it is in this context that I analyze terror. According to both cross-sectional regression analysis and generalized method of moments estimation techniques, terrorism risk is systematic and priced in the American financial market from January 1971 to December 2010 for nonindustry returns. This conflicts with previous research which uncovers the effects of terror reflected in industry returns (Choudry (2005) and Berrebi and Klor (2010)). Results further contrast when the data is separated into time periods before and after September 11, 2001. The lack of terrorism risk in the latter period suggests either measurement error of the terrorism index, incorrect assessment method, or both. Suggestions for future research include alternative measures of the terrorism index and the use of time-varying betas and conditional linear factor models in analysis.

In terms of the contributors to terror, I have determined that social parameters like education and democracy variables contribute more to terror than economic variables like income and employment rates. I further determined that the geographic location of a country positively contributes to terrorism. If terrorism is in fact suggestive of underlying political unrest, then examination of the determinants of terrorism is important because it is another means by which to mitigate future terror attack risk. Another avenue for future research is the discovery of the complete list of terrorism determinants and the incorporation of the contributing socioeconomic variables in asset pricing models.

Now, the outcome concerning risk premium in time period after 9/11 suggests that the number of terrorist attacks may no longer be a concern in the American financial sector. So is terrorism risk, and subsequently political risk, unnecessary in the pricing of financial assets? Or are investors just less afraid of terrorism since the epic attacks on the World Trade Center? One answer is, yes, investors are less afraid in the time since September 11, 2001 now that there is more awareness and policing of terror activity than in previous decades. On the 10th anniversary of September 11th, USA Today announced recent findings of its Gallup poll demonstrating a ten year low in American fear of an impending terrorist attack, but with little explanation as to why (Saad (2011)). While Americans are less concerned with terrorism, it is not due to an overconfidence in the protection provided by the American government. The Gallup poll further indicates that confidence in the Departments of Defense, Homeland Security, and State is not as great as it was in the time just after 9/11.

A second possibility is that with the increased, widespread attentiveness to terrorism and terror activity, investors are not so startled by the sheer number of domestic terror events but rather the national importance of individual events, such as September 11th itself. In 2009, the Washington Times published an article stating that the events of September 11th, 2001 while tragic, is only one of more than 1,000 events in the U.S. since the 1970s, which is supported by the GTD data (see Harper (2009) and GTD (2011)). The author suggests that the reaction to the event, the public perception and the stress and anxiety induced, has more of an effect on the national opinion of what constitutes terrorism and not necessarily the number of events. So perhaps this particular measure of terrorism risk in the time after September 11th is inaccurate. A measure that employs the significance of individual events or the effects of terrorism could yield interesting results.

A proper mimicking portfolio might also be an avenue for further inspection. Mimicking portfolios have been shown to perform better in financial analysis than nontraded factors, so the creation of a portfolio that mimics for terrorism risk using stock returns might yield even more interesting results (Balduzzi and Robotti (2008), Balduzzi and Robotti (2009), and Hou and Kimmel (2006)). Using the S&P 500, Karloyi (2007) develops his own set of “terrorism portfolios" and uses them to derive two terrorism-related investment strategies: the first is a portfolio of S&P 500 stocks assembled based on terrorism risk scores and the second are terrorism-related risk exposure portfolios. Both of these could be used as a stand-in for terrorism risk and the application is an avenue for future research.

Now, though results are inconclusive between the portfolio sets, this does not indicate that general political risk does not contribute to the price of stock returns. Terrorism risk is only one measure of political uncertainty. Further research and alternative measures of political risk, like the political regime change variable utilized in Chapter 3, are required before making that conclusion. The use of inappropriate estimation techniques for smaller samples could bias the data. That topic is also investigated further in Chapter 4.

Chapter 3

Political Risk: Estimating the Risk Premium of Political Regime Change

3.1 Introduction

A recent article by David Leonard of the New York Times suggests that the outcome of this year's presidential election would be dependent on the state of the economy (Leonard (2012)). According to the article, the most significant influence, historically, on American voters is the economic outlook. There is a longstanding relationship between politics and the economy. There is also a longstanding relationship between politics and the financial markets. On March 5, 2012, the Wall Street Journal published an article indicating that during presidential election years, the Dow Jones Industrial Average dips in the months preceding the election but rebalances once the election is over (Browning (2012)). This would suggest that uncertainty over the outcome of the election has a negative effect on investment, but once that uncertainty is mitigated, investors begin to reinvest.

Political uncertainty, or the uncertainty over the unknown costs of political events, decisions, and actions, is the result of changes in political policies and government leadership. The uncertainty induced from upcoming political events, such as elections, and its relationship with investment and the market has been investigated in Durnev (2011) and Julio and Yook (2012). In Durnev

(2011), analysis is performed on a large, international panel of elections and stock prices. The author concludes that investment is less sensitive to stock prices during election years due to noisier signals. Julio and Yook (2012) note a decrease in investment during election years, finding evidence to support the hypothesis that political uncertainty causes firms to reduce investment until electoral outcomes become known. Also in a panel investigation, Pantzalis, Strangeland, and Turtle (2000) find abnormal, positive returns in the two weeks prior to elections. And Born and Li (2007) support their hypothesis that uncertainty about U.S. presidential elections is reflected in pre-election common stocks. They further indicate that if there is no dominant candidate, stock market volatility and average returns rise.

Return volatility is investigated in Boutchkova, Dosh, Durnev, and Molchanov (2012). They determine a relationship between industry return volatilities, trade, and political uncertainty. The authors reason that those industries dependent on trade experience increased volatility when political risks are higher. They further suggest that while systematic volatility is associated with domestic uncertainty, global uncertainty is associated with idiosyncratic volatility and can thus be diversified even though this may not be necessary. Incidentally, the connection between various political policies, specifically tax policies, and trade has been investigated in papers like Handley and Limão (2012) where political uncertainty affects the firm's decision to enter into international trade.

But the question remains, does political risk, the uncertainty about the ramifications of possible government actions and policies, have a direct effect on asset prices? This paper examines that very question. I hypothesize that political risk is a contributing risk factor in the pricing of securities. I price this factor by first creating a variable that proxies for political risk and then perform cross-sectional and nonlinear regression estimation to examine the risk premium incurred. In general, few factors have been accepted as having an effect on asset prices wherein investors require compensation for holding securities that contain this risk. This investigation supports the argument that political risk is an important factor that cannot be overlooked in the pricing of assets. This is the first empirical exercise using standard multifactor asset pricing models to confirm the significance of political risk. My contribution also includes affirmation that average returns in excess of the risk-free rate are higher under a Democratic regime than a Republican regime.

It is difficult, if not impossible, to measure political risk. While uncertainty about particular government policies and the related costs are not easy to quantify, it is possible to measure political regime change. Though we cannot be certain which policies will be chosen nor the political costs of those policies, if we learn which regime is in control of the government at the time of the policy change, we will have some indication as to what type of policy is more likely and thus what type of costs to anticipate. If regime change is indeed a source of insecurity amongst investors, then there must be some empirical evidence to support the added risk of this uncertainty.

Within the United States, there are essentially two dominant political parties, Democrat and Republican, each with its own set of political agendas and general policies. To assess the effects of political regime change, I first examine the average excess returns of 25 portfolios organized based on size and book-equity to market-equity and 49 industry portfolios when the federal government is under the control of each respective political party. Analyses suggests that average excess returns are higher under a Democratic regime than a Republican regime.

While regime change might explain the variation in assets over time, it does not yet explain the cross section of returns. I create a dummy variable that represents the switching of regime from Democratic control of government to Republican and use it to analyze the cross sections of assets. I use both cross-sectional and multivariate nonlinear regression to estimate the risk premium of political regime change. Using monthly excess returns, I find that the risk premium is positively priced and in the case of the 25 portfolios, it accounts for the variation in returns along with the Fama-French factors (Fama and French (1993)). In the case of the 49 industry portfolios, political risk is the only factor that maintains a risk premium and is thus the only factor that explains the variation in excess returns.

3.2 Related Literature

To my knowledge there are just two papers, both by Ľuboš Pástor and Pietro Veronesi, that address the measurement of political uncertainty theoretically. In both, the authors produce a general equilibrium model of government policy using the price of political risk, however, the models differ in their use of homogenous and heterogenous government policies. In Pástor and Veronesi (2012), the authors use homogenous policies and find that the model indicates a decrease in stock prices after the announcement of a policy change. The magnitude of this decrease is large if the uncertainty about the government policy is large. Policy changes also increase the volatilities and correlations of stocks, and the jump risk premium, or the jump in stock prices on the date of the policy change announcement, should be positive. The results in Pástor and Veronesi (2011) are similar, however, the government policies are heterogenous.

The model in Pástor and Veronesi (2011) specifies that stock prices are driven by three types of shocks: capital shocks, impact shocks, and political shocks. The first two shocks are referred to as economic shocks and they are driven by shocks to aggregate capital. The last shock, political shocks, are orthogonal to economic shocks and thus command their own risk premium. Political shocks are the result of learning about political costs, the uncertainty of which Pástor and Veronesi refer to as political uncertainty, of prospective policies. The shocks reflect the flow of news about the various government policies, which in turn leads investors to modify their beliefs about the likelihoods of the policies. Through simulations, the authors determine that the political risk premium is larger in a weaker economy and directly contributes to the jump risk premium at the time of the policy change announcement, which is generally positive.

While Pástor and Veronesi (2011) and Pástor and Veronesi (2012) both introduce a model that suggests that political risk is indeed a priced risk factor, the literature on political cycles does not necessarily corroborate this suggestion. Using a time series of excess returns, Huang (1985) and Santa Clara and Valkanov (2003) find that there is a difference in the averages contingent upon the administrating party in the White House, often referred to as the partisan cycle. Democratic presidencies yield higher than average excess returns when compared to Republican presidencies.

In Huang (1985), the author examines stock returns over the four-year election cycle, discovering that returns are smaller in the first two years than in years three and four. Huang suggests a risk hedging mechanism, investing only in treasuries during cycle years one and two of a Republican administration. But he stops short of estimating a risk premium. Santa Clara and Valkanov (2003) corroborate the results of Huang (1985) but attribute the higher average returns to business cycle fluctuations. They further propose that increased return volatilities under the Republican presidencies indicates no evidence for a Democratic risk premium.

These arguments are further expanded by Belo, Gala, and Li (2012). They discover that industries with amplified exposure to government spending experience higher average returns during a Democratic presidency. The authors construct a new measure of industry exposure to government spending using data on input-output accounts. Unconditionally, there is no difference in average returns with heterogenous exposure, however, there is variation in the averages conditional on the presidential partisan cycle. Additionally, by constructing an investment strategy based on the partisan cycle, they discover that the differences in return levels is due to abnormal returns.

This research is similar to the previous research in that I search for a connection between political risk and asset pricing, finding a relationship between the controlling political party and average excess returns. I generally confirm the results of Pástor and Veronesi (2011) by finding a positive relationship between political uncertainty and assets. But unlike both Pástor and Veronesi articles, which are highly theoretical, I formulate an empirical measure of political risk and test it using a standard multifactor asset pricing model.

I confirm the results of Belo, Gala, and Li (2012), Huang (1985), and Santa Clara and Valkanov (2003) by determining that average excess returns are greater under a Democratic presidency than a Republican, but I supplement these results using a measure of both the executive and legislative branches of government with not only industry portfolios but common stock returns organized based on size and book-to-market equity and not government exposure. I do not focus on the business or partisan cycle. Belo, Gala, and Li (2012) emphasize the role of exposure to government spending in predicting the cross section of returns exploiting the predictability of a presidential partisan cycle investment strategy. But unlike this endeavor, the authors do not price political risk in a linear factor model as I do. I hypothesize that political risk is priced and I discover a risk premium that is positive and significant. While my results differ empirically from those of the three preceding articles, they provide the motivation for this study.

The greater difference between this endeavor and the previous empirical research is the assessment of political uncertainty. All three papers would suggest that because Democratic administrations experience larger excess returns over Republican administrations that stock returns are riskier under this regime and safer under the other. This is not the suggestion of this paper. I do not seek to discover the “Democratic risk premium". My hypothesis is in agreement with Pástor and Veronesi (2011), the political uncertainty to assess is the uncertainty of the future unknown costs of the relevant political policies and their affects on security returns. So in the next section, I capture political risk by indexing political regime change. While we cannot be certain about what policy will be chosen nor what the costs of those policies will be, if we learn which regime, or political party, is in control of the government at the time of the policy change, we have some indication of what type of policy is more likely and thus what political costs to anticipate. This serves as the measure of political risk throughout this empirical exercise.

3.3 Average Excess Returns and Regime Switching

In order to create the political regime change variable, which I use as a proxy for political risk, I must first assess if there is indeed a difference in the average excess returns under each regime. Arguably, any difference could be attributed to concerns over the proposed policies and subsequent costs of the dominating party. For this part, I focus on the American political system, particularly, the predominant two-party system that the United States maintains and their control of the lawmaking branches of the government. I hypothesize that there is a difference in average excess returns under the governmental control of the two political parties, Democrat and Republican, with previous research indicating higher averages under the Democratic regime (Santa Clara and Valkonov

(2003)).

3.3.1 Analysis: Democrat versus Republican

Within the United States there are three branches of government: the executive branch, the legislative branch, and the judicial branch. While the judicial branch created and maintains the court system and is considered the law-enforcing portion of the federal government, it is not a lawmaking branch of government. So I focus my analysis on those two branches that are legislative as political influence on these branches directly influences the laws and policies that are created.

The other two branches of the government, the executive and legislative branches, are both lawmaking branches although their functions in the legislating process are quite different. The executive branch consists of the White House which is controlled by the President and his cabinet. The legislative branch, or Congress, consists of two houses, the Senate and the House of Representatives, comprised of members elected by the American public (currently 100 senators, two from each state, and 435 representatives, the number of which depends on the population of the individual state). Unlike the White House, neither house is controlled by any individual member but rather a ruling majority. Obviously, each of the three houses, the White House, the Senate, and the House of Representatives, is directly influenced by the political party of the ruling majority. In the case of the White House, the President's political party will have amplified influence on the entire executive branch.

I obtain presidential and congressional data from 1927 through 2009 (see About.com (2012) and Infoplease (2012)). In order to analyze the differences in average excess returns based on party control, I employ the definition of party control as “majority vote" or the party that sustains the majority of members within the house. For the most part, majority vote consists of the party with more than 50% of the seats, but for a few years, majority vote was either at or below 50%. Of course, control of the White House belongs to the party with whom the President is affiliated.

For the testing assets, I use the 25 portfolios, 49 industry portfolios, and the excess market return obtained from Kenneth R. French's data library (French(2012)). The 25 portfolios are assembled at the end of June and consists of NYSE, AMEX, and NASDAQ stock returns. They are formed by the intersections of five portfolios generated based on size and five portfolios generated based on book-to-market equity. The 49 industry portfolios are created due to the assignment of each stock to an industry using its Compustat SIC code. They are unorganized and I exclude industries 3, 11, 15, 20, 26, 27, 36, and 39 from the analysis for a lack of historical data. I use these portfolios because of their accessibility and portfolio organization, both useful characteristics for econometric analysis later on. For each set of portfolios, I calculate the excess returns (the portfolio return in excess of the risk-free rate) and analyze the averages using monthly and annual data.

I use three categories to analyze the extent of each party's control of the federal government: the executive branch (the White House), the legislative branch (both the Senate and the House of Representatives), and both branches (the White House and at least one house of Congress). With these categories, there is some amount of overlap in the years utilized because the year of control is counted regardless of which party is in control of the other houses. Now, while the Democrats controlled the executive branch for about the same length of time as the Republicans, the Democrats controlled the legislative branch for about twice as long as the Republicans and ten years longer for both branches (for details, see Appendix B).

I calculate average excess returns and other relevant statistics during each regime's control of the relevant branch in Table 3.1 (also see Appendix B for detailed statistics). In all three cases, the Democratic Party sees significantly higher than population average excess returns while the Republican Party sees lower than average. Incidentally, the Democratic Party's returns are at least twice the size of the Republican returns. Particularly, when the Democrats control both branches, the average annual returns for the 25 portfolios are around 20%, but when the Republicans control the government averages are just under 3%. Both are significantly different from the population average for the 25 portfolios for the length of the sample.

Interestingly, while the average excess returns for the 49 industry portfolios are always smaller than the average returns for the 25 portfolios when the Democrats are in control, the average excess returns for both sets of portfolios are much closer under Republican control. This speaks to the Republican Party's well-known platform that supports industry, small-business, and private investment over government spending. However, all of the earlier results reject the popular notion that average excess returns are better under a Republican administration than a Democratic administration.

Table 3.1: **Average Excess Returns Under Regime Control**

	Executive Branch		**Legislative Branch**		**Both Branches**	
Democrat	Avg Return	Variance	Avg Return	Variance	Avg Return	Variance
Annual						
25 Portfolios	18.324	887.852	13.752	986.402	20.321	1011.864
49 Industry	15.211	907.083	11.598	972.886	16.563	992.527
Mkt Return	12.822	331.884	9.089	419.484	13.005	363.21
Monthly						
25 Portfolios	1.445	67.474	1.035	59.354	1.593	75.727
49 Industry	1.172	56.702	0.852	53.903	1.269	60.587
Mkt Return	1.015	27.461	0.698	26.573	1.032	29.387
Republican						
Annual						
25 Portfolios	4.462	850.59	5.796	869.257	2.744	921.953
49 Industry	4.407	933.318	5.826	1002.502	2.73	1060.954
Mkt Return	3.142	514.531	5.744	584.379	1.09	623.595
Monthly						
25 Portfolios	0.211	66.667	0.315	99.441	0.032	97.363
49 Industry	0.259	60.454	0.396	77.8	0.11	78.208
Mkt Return	0.214	32.218	0.437	41.813	0.048	42.532

The average excess market return is usually never significantly different from the population average at more than the 10% level, but it is a good indication of how the market in general performed during each administration. It follows the same pattern as the 25 portfolios and the 49 industry portfolios. Return volatilities are also about the same regardless of regime control, with Republican control just slightly higher.

3.3.2 Political Regime Change

There does seem to be some truth to regime change and its effect on average excess returns. The inference is that the regime changing reflects the uncertainty investors feel regarding the outcome of elections (and subsequently future political actions and decisions), more specifically, whether Democrats will control the federal government or the Republicans. To account for the regime changing, I create a dummy variable marking '1' for the years the Republicans control the government, in this case two or more of the three lawmaking houses (the White House, the Senate, or the House of Representatives), and '0' otherwise, corresponding to Democrat control of two or more houses.

After creating the dummy variable for the entire length of the time series, I want to examine average excess returns once again, to ensure that the differences between the two regimes is captured by the new variable. By definition, it is not possible for both parties to control the government simultaneously, so there is no overlap in time periods. Republicans control the government for 29 years of the series and Democrats control for 54 years (see Appendix C). Once again, the 25 portfolios, 49 industry, and the market return are utilized on annual and monthly excess returns. The results in Table 3.2 are similar to the previous section, however, the difference in average excess returns is not quite as large as before. But the relationship is maintained–Democrats see higher than average excess returns and Republicans see lower than average. Volatilities are about the same as before.

It is apparent that the new dummy variable, which I now refer to as the regime change dummy, does a good job capturing the relationship between the averages under the respective regimes. Now, average excess returns indicate an interesting result, that the stock market is better off with a Democratic government than a Republican government. This is true under a time series of 25 portfolios, 49 industry portfolios, and the market return. But does regime change uncertainty also affect the cross section of returns? Does the regime change dummy account for the variation across assets as well as it does for the time series? Before we can conclude that regime change is an appropriate proxy for political risk and is thus a priced risk factor in asset pricing, we must first analyze its effect on the cross section of security returns.

Table 3.2: **Average Excess Returns Under the Regime Change Dummy Variable**

Democrat(0) *Annual*	Average Return	Variance
25 Portfolios	14.111	997.127
49 Industry	11.927	983.341
Mkt Return	9.343	423.761
Monthly		
25 Portfolios	1.062	60.23
49 Industry	0.876	54.563
Mkt Return	0.717	26.899
Republican(1)		
Annual		
25 Portfolios	6.092	726.012
49 Industry	5.679	861.188
Mkt Return	5.281	483.728
Monthly		
25 Portfolios	0.371	80.575
49 Industry	0.401	66.567
Mkt Return	0.41	35.803

3.4 Methodology

Consider the basic pricing formula, $p_t = E[m_{t+1}x_{t+1}]$ or equivalently $1 = E[m_{t+1}, R_{t+1}]$ where $R_{t+1} = \frac{x_{t+1}}{p_t}$ are gross returns on assets (Cochrane (2005)). Asset pricing models usually only differ in their interpretation of the stochastic discount factor, m_{t+1}. An important class of asset pricing models is the linear factor model, or the linear beta pricing mode, which interprets the stochastic discount factor as a linear combination of various pervasive risk factors in the form of $m = b_0 - f'b_1$ (in this example, I use a single factor and I eliminate the time subscripts for simplicity). It can be shown that the linear beta restriction is equivalent to the linear stochastic discount factor assumption (Cochrane (2005)). Excess returns can also be used in place of gross returns to simplify analysis, but the use of excess returns requires slightly different initial assumptions: $m = 1 - b(f - E[f])$ (see Chapter 4 for further details). To test whether political regime change risk accounts for the variation in the cross section of asset returns, I utilize excess returns in standard linear factor asset pricing model.

Denote by R_t a vector of returns in excess of the risk free rate on N assets at time t and f_t as the vector of K economy-wide factors at time t. Now assume that returns follow the linear process

$$R_{i,t} = \alpha_i + f_t'\beta_i + u_{i,t}, \quad i = 1,\dots,N, \quad t = 1,\dots,T \tag{3.1}$$

where the errors $u_{i,t}$ are uncorrelated with the factors for all i with mean zero and β_i is the vector of betas, or factor loadings, for asset i which is given by

$$\beta_i = E[(f_t - E[f_t])(f_t - E[f_t])']^{-1} E[(R_{i,t} - E[R_{i,t}])(f_t - E[f_t])], \tag{3.2a}$$

$$\Sigma_R = E[(R_{i,t} - E[R_{i,t}])(R_{i,t} - E[R_{i,t}])'], \tag{3.2b}$$

$$\Sigma_f = E[(f_t - E[f_t])(f_t - E[f_t])']. \tag{3.2c}$$

Under these assumptions, the linear beta pricing model places the restriction

$$E[R_{i,t}] = a_0 + \lambda'\beta_i, \quad i = 1,\dots,N \tag{3.3}$$

where λ is the vector of risk premia and a_0 is a vector of constants (see Jagannathan, Schaumburg, and Zhou (2010)). Another way to interpret the two equations above is to consider the factor loadings, β_i, as the relationship between the risk factors, f_t, and the returns, R_t. Then λ can be interpreted as the price of risk or the amount of compensation that investors require for holding onto assets with the risk factors present. If λ is positive and significant, then we would say that the factor is priced because it does explain the variation in the cross section of asset prices.

Classic articles by Chen, Roll, and Ross (1986) and Fama and French (1993) use linear factor models to explain the cross sections of assets, each with their own risk factors. While Chen, Roll, and Ross use macroeconomic variables in their analysis, Fama and French create mimicking portfolios that capture the pervasive risks presented by firm characteristics such as firm size and book-to-market effects. Along with these two factors, Fama and French also use the market portfolio in excess of the risk-free rate to create the Fama-French factors which are now commonly used in empirical studies as they do indeed account for much of the variation in the cross section of security returns.

3.4.1 Cross-Sectional Regression

There are several methods to evaluate linear factor models, two of which I employ in this empirical investigation (I follow the notation of Jagannathan, Skoulakis, and Wang (2010)). The first is the simplest and most robust, cross-sectional regression which I first used in Chapter 2. Cross-sectional regression estimation is based on the Fama-MacBeth technique developed in Fama and MacBeth (1973) to assess the relationship between expected returns and factor betas (Jagannathan, Skoulakis, and Wang (2010)). It is performed in two passes, which is why it is generally referred to as "two-pass regression". The first pass is a time series regression to estimate the relationship between the returns and the factor loadings (betas). The second is a cross sectional regression to measure the relationship between the factor loadings and average returns.

Consider the following reinterpretation of the beta representation,

$$E[R_t] = a_0 1_N + B\lambda = Xc \tag{3.4}$$

where

$$X = [1_N \quad B], \quad c = [a_0 \quad \lambda']', \tag{3.5}$$

X is a N x $(K+1)$ matrix and c is a $(K+1)$ vector of risk premia. Then standard OLS estimation of c yields

$$c = (X'X)^{-1}X'E[R_t]. \tag{3.6}$$

Two-pass regression is essentially the same estimation technique as Fama-MacBeth estimation, only in a slightly different form. Unlike Fama-MacBeth, which estimates a separate risk premium $\hat{c}_t$ over the full cross section at each time period in the second pass and then averages over all estimates, cross-sectional regression estimates a single $\hat{c}$ over the full time series using an average of the returns for each cross section. Both forms yield identical results for $\hat{c}$ and $Var(\hat{c})$ making them equivalent and interchangeable estimation methods (Kleibergen (2009) and Jagannathan, Skoulakis, and Wang (2010)).

Regression can be performed either with or without the constant a_0. Per theory, this vector should equal the zero-vector. If regression is run allowing for estimation of the constant, then the parameter can be tested for significance (Cochrane (2005)). If the model is correctly specified, then $a_0 = 0_N$ (Jagannathan, Schaumburg, and Zhou (2010)). Most researchers prefer to estimate the constant along with the other parameters as a test of model validity.

We can further work backwards from the definition of B and write the time-series regression as

$$R_t = E[R_t] + B(f_t - E[f_t]) + u_t \tag{3.7}$$

where u_t has mean zero and is uncorrelated with the factors. If we substitute for the expected returns the beta pricing restriction, then we derive the return process

$$R_t = a_0 1_N + B(f_t - E[f_t] + \lambda) + u_t \tag{3.8}$$

Of course, two-pass estimation is robust and easy to apply in large samples, however it does impose assumptions that are not overly realistic and, the larger problem, the second pass estimation requires the use of an estimated regressor causing the classic error-in-the-variables problem.

The standard assumptions for this estimation process include conditional homoskedasticity, which holds when the returns and factors are identical and independently normally distributed (Jagannathan, Schaumburg, and Zhou (2010)). This is a nice assumption because standard t-tests can then be calculated to test the validity of the relevant coefficients. But there is some empirical evidence to indicate that returns are actually heteroskedastic, nonnormally distributed, and even autocorrelated.

The error-in-the-variables problem is also not one that can be overlooked. There are several prescribed methods for compensating for this problem. One method is to use portfolios instead of individual stocks as the testing assets. It is believed that the large number of stocks employed are estimated precisely enough to compensate for the error. Another method, suggested by Fama and Macbeth (1973), is to estimate a separate variance matrix accounting for the error in the second stage, however, this method has proven to overstate the precision of estimates and is subsequently inefficient under the assumption of conditional homoskedasticity. And yet another method is to use generalized least squares in the second pass of estimation. c is then formed as

$$c = (X'QX)^{-1}X'QE[R_t] \tag{3.9}$$

where Q is positive definite N x N matrix. With this method, portfolio formation may not even be necessary. This is the method I utilize to account for the error-in-the-variables problem in the empirical section.

3.4.2 Nonlinear Regression

It is controversial for some researchers to not only estimate risk premia in two passes, but to use estimated regressors in the second pass. So for this reason, I employ the use of multivariate nonlinear estimation to calculate betas and lambdas simultaneously. I follow the nonlinear least squares method as suggested in two papers by Burmeister and McElroy (1988). Nonlinear estimation delivers, even in the absence of normally distributed errors, estimates that are consistent and asymptotically normally distributed, all of which can be tested using standard hypothesis testing methods.

Remember the return process generated in the previous section, ignoring the constant for the time being:

$$R_t = B(f_t - E[f_t] + \lambda) + u_t \tag{3.10}$$

Now consider the regeneration of the process:

$$r_i = [(\lambda' \otimes \iota_T) + F]b_i + u_i, \tag{3.11}$$

where r_i are the excess returns for asset i from time $t = 1, \ldots, T$, λ are the risk premia for the K factors, ι_T is a vector of T ones, F is the matrix of K demeaned factors from time $t = 1, \ldots, T$, b_i is the vector of betas for asset i, and u_i is the error component with mean zero for asset i from time $t = 1, \ldots, T$.

Nonlinear least squares estimation works by solving each individual equation i for β_i and λ concurrently. However, the use of nonlinear seemingly unrelated regression allows us to solve all equations simultaneously (Burmeister and McElroy (1988)). Further simplification implies

$$r_i = \chi(\lambda)b_i + u_i, \tag{3.12}$$

where $\chi(\lambda) = (\lambda' \otimes \iota_T) + F$. Stacking each equation yields

$$\begin{pmatrix} r_1 \\ \vdots \\ r_N \end{pmatrix} = \begin{bmatrix} \chi(\lambda) & & 0 \\ & \ddots & \\ 0 & & \chi(\lambda) \end{bmatrix} \begin{pmatrix} b_1 \\ \vdots \\ b_N \end{pmatrix} + \begin{pmatrix} u_1 \\ \vdots \\ u_N \end{pmatrix} \tag{3.13}$$

or

$$R = [I_N \otimes \chi(\lambda)]B + u \tag{3.14}$$

where $E[u] = 0_{N,T}$ and $E[uu'] = [\Sigma \otimes I_T]$. (3.14) is the NLSUR formula on which nonlinear least squares is utilized.

3.5 Empirical Results

3.5.1 Cross-Sectional Regression

For the empirical estimation of the cross-sectional regression, I utilize the monthly excess returns for the 25 portfolios and 49 industry portfolios. I perform regression on four scenarios of risk factors using different combinations of the regime change dummy and the Fama-French factors, the excess market return, the size mimicking portfolio Small-Big, and the book-to-market equity mimicking portfolio High-Minus-Low (details on the Fama-French factors were discussed in Chapter 2). Not only is it important to understand if the regime change factor is priced but if it is priced in the presence of other well-known risk factors.

The regime change dummy performs well in the estimation for the risk premia of the 25 portfolios. The dummy risk premium is approximately the same for each of the four scenarios of risk factors, at approximately 0.35% on average. This is also in agreement with the amounts of the other risk premia. In the second scenario, the regime change dummy, while valid, does not require as much compensation as the market return. In the third scenario, the dummy requires a little more compensation than the factors that mimic for risks related to firm characteristics, though just slightly. In the fourth scenario, all of the four factors are employed and all are statistically valid with the regime change parameter requiring less compensation for risk than the other factors. Interestingly, in three of the four scenarios the intercept term is indeed different from zero. This would imply model misspecification if the errors are not also jointly zero (Cochrane (2005)). The second scenario, which considers the regime change dummy and the excess market return as the sole risk factors in the economy, is the only instance of a zero constant term. The intercept term is also the largest in the fourth scenario which engages all four risk factors.

Table 3.3: **Risk Premia(λ_i) Results Using Cross-Sectional Regression Estimation**

Portfolios	Regime Change	Market	Small-Big	High-Low	Constant
25 Portfolios	0.324***				1.045***
	(4.31)				(14.66)
	0.376***	0.81***			0.089
	(5.75)	(3.20)			(0.29)
	0.389***		0.203***	0.333***	0.587***
	(8.36)		(3.54)	(4.18)	(7.16)
	0.355***	-1.357***	0.499***	0.536***	1.715***
	(9.51)	(-3.99)	(5.76)	(6.66)	(5.92)
49 Industry	0.196***				0.803***
	(4.56)				(26.65)
	0.224***	0.264**			0.538***
	(5.39)	(2.49)			(4.90)
	0.300***		0.241**	-0.067	0.704***
	(4.88)		(2.22)	(-0.68)	(11.80)
	0.249***	0.312*	0.062	-0.14	0.516***
	(3.76)	(1.74)	(0.42)	(-1.35)	(4.21)

Two-pass regression using monthly excess returns: OLS first pass, GLS second pass. z-statistics are reported in parenthesis below regression estimates. ***significance at the 1% level, **significance at the 5% level, *significance at the 10% level. Portfolios obtained from Kenneth R. French's website.

Results are not as clear for the estimation of the risk premia for the 49 industry portfolios. Notice that the risk premium of the regime change dummy in all four scenarios is not quite as large as it was for the 25 portfolios at approximately 0.23% on average. It maintains significance throughout the scenarios, however, results are not the same for the other factors. The model performs well in the second scenario with the risk premia for both the regime change and the market factors about equal. The same applies for the third scenario between the risk premia for the regime change and size factors, however, the book-equity to market-equity factor maintains insignificant risk premium implying that in this scenario it is no longer a risk factor. In the final scenario, the regime factor and the excess market factor are the only two that have significance. In all four scenarios, the constant term is statistically different from zero.

The inconsistent results for the 25 and 49 portfolios are interesting. The first estimation would suggest the political risk in the form of regime change is indeed another risk factor that, along with the Fama-French factors, can be utilized in asset-pricing theory. But these results are not as clear in the case of the 49 industry portfolios. The final regression could suggest that political uncertainty is much more of a concern for industries than firm characteristics and the market, though the market is still important. This can be profound for industry investment. Coupled with the results obtained in previous research such as Belo, Gala, and Li (2012) and in Chapter 2, further investigation into political risk and industry analysis is well-warranted.

3.5.2 Nonlinear Regression

The results for the nonlinear estimates of risk premia are not too different from the cross-sectional estimates. The risk premium for the regime change dummy variable is still approximately 0.35% for the 25 portfolios maintaining significance throughout all four scenarios. Similar results are also derived for the 49 industry portfolios with a risk premium at approximately 0.23% throughout.

The difference between these results and the previous occurs in the estimation of the risk premia for the Fama-French factors. For the 25 portfolios, the premia for the factors is generally smaller than what is suggested by cross-sectional regression analysis, which could be due to an understatement of standard errors using that method. They are also only valid in the final scenario with all four factors present. But this does corroborate the prior assertion that along with the Fama-French factors, political risk explains the cross section of returns (we also saw this with the 100 portfolios in the time after 9/11 in Chapter 2). Now, for the 49 industry portfolios, estimates are again much smaller in each scenario, which encourages the belief that political risk has much more of an effect on the pricing of industry assets than the Fama-French factors. The constant is also statistically different from zero in all scenarios for both sets of assets.

It is also a possibility that the loss of significance in the estimation of risk premia is due to estimation error or small sample bias. The use of nonlinear least squares could be skewing the results as nonlinear estimation tends to perform better with larger samples. For these reasons, an investigation into the effectiveness of nonlinear estimation, particularly generalized method of moments estimation, on small samples is investigated in Chapter 4.

Table 3.4: **Risk Premia(λ_i) Results Using Nonlinear Regression Estimation**

Portfolios	Regime Change	Market	Small-Big	High-Low	Constant
25 Portfolios	0.324***				1.494***
	(0.075)				(0.11)
	0.328***	0.043			1.443***
	(0.087)	(0.08)			(0.154)
	0.349***		0.03	0.151	1.374***
	(0.114)		(0.122)	(0.182)	(0.157)
	0.366***	-0.684***	0.369**	0.49**	1.528***
	(0.103)	(0.242)	(0.161)	(0.204)	(0.175)
49 Industry	0.196***				1.112***
	(0.043)				(0.06)
	0.192***	0.022			1.083***
	(0.051)	(0.039)			(0.076)
	0.245***		0.119	-0.127	1.109***
	(0.074)		(0.11)	(0.152)	(0.079)
	0.243**	0.002	0.113	-0.132	1.114***
	(0.116)	(0.195)	(0.249)	(0.183)	(0.1)

Nonlinear least squares regression using monthly excess returns. Standard errors are reported in parenthesis below regression estimates. ***significance at the 1% level, **significance at the 5% level, *significance at the 10% level. Portfolios obtained from Kenneth R. French's website.

3.6 Conclusion

Due to the difficulty of measuring political risk, I chose to use a variable that measures regime change, or the change from the Republican Party's control of the lawmaking portion of the federal government to Democrat. I examined the control, or voting majority, of two or more houses of the federal government by either party during the time period between 1927 and 2009. Portioning the data as such, I analyze the average excess returns of portfolios organized on size and book-to-market equity along with various industry portfolios, and all are consistently larger under a Democratic regime than a Republican regime. A dummy variable was then generated to account for the change of government control from one political party to the other. This variable is the regime change variable, which is a proxy for political risk.

Though regime change seems to have an effect on the time series of average excess returns, further analysis was required to verify if political uncertainty has a similar effect on the cross section of returns. I performed cross-sectional analysis on the monthly excess returns for the 25 portfolios and 49 industry portfolios using two-pass regression and nonlinear least squares. I discovered that for the 25 portfolios the regime change variable, in the presence of the Fama-French factors, is a priced risk factor. But results were not the same for the 49 industry portfolios. In fact, when combined with the Fama-French factors, the regime change variable was the only valid risk factor implying that this variable requires more compensation for risk than factors related to firm characteristics and is thus more important in the pricing of industry assets than the other factors.

Further research will be required to make any conclusive arguments about the validity of the regime change variable and its approximation of political risk. The inconsistency between the results for the 25 portfolios and the 49 industry could be due to either variable mismeasurement or small sample bias. It has been shown that mimicking portfolios created to proxy for nontraded factors are more efficient and precise in the pricing of assets than variables that are not also returns (see Balduzzi and Robotti (2008), Balduzzi and Robotti (2009), and Hou and Kimmel (2006)). So another avenue for future research is to create a set of proper mimicking portfolios that proxy for the regime change. Or perhaps an alternative variable such as a direct measure of political news as suggested by Pástor and Veronesi (2011) could be utilized. Eldor and Melnick (2004) use measures of news in their discovery of the effect of media coverage on terrorism. Though this might yield statistically interesting results, an economic model would also need to be developed to further corroborate these results on a theoretical level (see Pástor and Veronesi (2011) and Pástor and Veronesi (2012)).

Chapter 4

A Comparison of Regression-Based and Generalized Method of Moments Estimation of Linear Factor Model Risk Premia

4.1 Introduction

In the previous chapters, I have estimated the risk premia of linear factor models using both regression-based and nonlinear methodologies. In Chapter 2, I assessed the risk premium of the political factor terrorism risk finding significance with nonindustry returns in the time period from January 1971 through December 2010 and the time period before September 11, 2001. I used generalized least squares regression and two-step generalized method of moments estimation in that analysis. In Chapter 3, I discovered the significantly priced risk premium of the political regime change dummy variable, another political factor. The results were obtained for data from 1927 through 2009 using generalized least squares estimation and nonlinear least squares regression.

But the question remains, are these results spurious? Assuming that the factors themselves are correctly measured, could the significant results all be due to inappropriate estimation methods? Regression-based estimation has performed well in previous analyses and results are more robust in larger samples (Jagannathan, Skoulakis, and Wang (2010)). But GMM has demonstrated more capability in estimation with conditionally heteroskedastic and serially correlated data.

To assess which method is more reliable in smaller samples, I test each using monte carlo simulations. I compare ordinary least squares regression, generalized least squares regression, two stage generalized method of moments estimation, and iterated generalized method of moments estimation using a two-factor model: the political regime change dummy factor and excess market return factor, both from Chapter 3. I simulate each factor to 960 observations, calibrated based on the true factors, and using prespecified risk premia, I generate twenty-five returns according to the linear factor model data-generating process. I discover that the regression-based methods perform better in smaller samples than the generalized method of moments techniques. Generalized least squares also slightly outperforms ordinary least squares in terms of rejection rates, however, OLS produces better point estimates. There is little difference between two-step GMM and iterated with both methods exhibiting small sample bias.

I further test the abilities of each methodology by setting each risk premium to zero in simulation. I find that all four methods tend to overreject the correctly specified null hypothesis, which is consistent with previous results for GMM estimation. This indicates the need to exercise caution in the determination of risk factors. To find true risk factors, it is important to base analysis on economic theory and not statistical properties alone. Point estimates are reassuring in this sense because while factors may be found to be statistically significant, they are economically meaningless.

4.2 Related Literature

There are many methods to estimate the risk premia of linear factor models, so subsequently, there are several examinations and assessments of those same methods, though comparisons across methodologies is rare. The first set of assessments focus on two-pass procedures. Kleibergen (2009) tests the risk premia of linear factor models obtained through the Fama-MacBeth technique. He determines that risk premia can be biased when betas are small or the number of assets is large. Kan and Zhang (1999) study the risk premia derived by least squares methods by testing the significance levels of useless factors. They find that these premia are too often significantly priced. Shanken and Zhou (2007) test beta pricing models by examining the estimators of ordinary, generalized, and weighted least squares methods discovering more precision with the GLS estimator but also more bias. The authors further provide more robust results by comparing the previous to generalized method of moments and maximum likelihood techniques finding maximum likelihood performing well in terms of bias and precision, though not as well as ordinary least squares.

Generalized method of moments techniques are more rigorously tested than are two-pass procedures. Kan and Zhou (1999) evaluate GMM estimates of risk premia by comparing the standard beta model with the stochastic discount factor specification discovering better results with the beta model (Jagannathan and Wang (2002) later counter this finding no difference between models under the correct framework). Ferson and Foerster (1994) have examined the finite sample properties of GMM by focusing on two-stage GMM and iterative. They find superior results with iterated generalized method of moments. This is extended by Hansen, Heaton, and Yaron (1996) and Peñaranda and Sentana (2010) who, along with the previous, also examine the continuously-updating GMM discovering the best estimates with the latter.

Along with the estimation methods themselves, specification tests are also evaluated by Ahn and Gadarowski (2004) and Kan and Robotti (2008). Under GMM estimation there are two commonly used tests for model validity: the Hansen-Jagannathan distance and the J-statistic (also known as the Hansen test). Ahn and Gadarowski (2004) find that the HJ-distance too often rejects correctly specified models while the J-statistic only mildly overrejects. Kan and Robotti (2008) use the stochastic discount factor specification to test the HJ-distance. The authors conclude that an incorrect framework for the SDF has an effect on the HJ-distance statistic and that modification of the statistic is required when using excess returns in estimation.

Unlike the previous analyses, which mostly focus on differing specifications of the same technical exercise, this endeavor directly compares cross-sectional regression to generalized method of moments estimation of risk premia under two specifications using simulations of small samples. Shanken and Zhou (2007) provide the only other simulated comparison of both methods, but they focus on the two-stage GMM excluding the iterative, which has been shown to be more precise in previous research (Ferson and Foerster (1994)). For cross-sectional regression, I demonstrate the Fama-MacBeth technique under both ordinary least squares and generalized least squares estimations. For generalized method of moments procedures, I use two-step and iterative GMM. I test the abilities of these estimators by generating twenty-five returns under a two-factor model using simulations of the political risk factor and market return factor from Chapter 3. I find that the regression-based methodologies outperform the generalized method of moments estimators in terms of point estimates and power. But I also discover that all four procedures tend to overreject a true null hypothesis.

4.3 The Linear Beta Pricing Model

Before we begin, it is important to understand linear factor models and the beta pricing restriction. Most asset pricing models are simply variations of the general pricing formula wherein price today is equated to expected future discounted payoff: $p_t = E[m_{t+1}x_{t+1}]$ or equivalently $1 = E[m_{t+1}, R_{t+1}]$ where $R_{t+1} = \frac{x_{t+1}}{p_t}$ are gross returns on assets (Cochrane (2005)). Asset pricing models usually only differ in their interpretation of the stochastic discount factor m_{t+1}. An important class of asset pricing models is the linear factor model which interprets the stochastic discount factor as a linear combination of various pervasive risk factors in the form of $m = b_0 - f'b_1$ (in this example, I use a single factor and I eliminate the time subscripts for simplicity). It has been previously shown that the beta pricing restriction is equivalent to the linear stochastic discount factor assumption (see Cochrane (2005)).

Estimation is further simplified with the use of excess returns in place of gross returns, although the use of excess returns requires slightly different initial assumptions. Under excess returns, the mean of the stochastic discount factor cannot be identified (Kan and Robotti (2008)). So some normalization of the discount factor is warranted: $E[m_{t+1}r_{t+1}] = 0$ where $m = 1 - b[f - E(f)]$ and r are returns in excess of the risk-free rate. Notice that this requires that returns and factors be demeaned in estimation (Jagannathan and Wang (2002) and Kan and Robotti (2008)).

Denote by R_t a vector of returns in excess of the risk free rate on N assets at time t and f_t as the vector of K economy-wide factors at time t. Now assume that returns follow the linear process

$$R_{i,t} = \alpha_i + f_t'\beta_i + u_{i,t}, \quad i = 1,\dots,N, \quad t = 1,\dots,T \tag{4.1}$$

where the errors $u_{i,t}$ are uncorrelated with the factors for all i with mean zero and β_i is the vector of betas, or factor loadings, for asset i which is given by

$$\beta_i = E[(f_t - E[f_t])(f_t - E[f_t])']^{-1}E[(R_{i,t} - E[R_{i,t}])(f_t - E[f_t])], \tag{4.2a}$$

$$\Sigma_R = E[(R_{i,t} - E[R_{i,t}])(R_{i,t} - E[R_{i,t}])'], \tag{4.2b}$$

$$\Sigma_f = E[(f_t - E[f_t])(f_t - E[f_t])']. \tag{4.2c}$$

Under these assumptions, the linear beta pricing model places the restriction

$$E[R_{i,t}] = a_0 + \lambda'\beta_i, \quad i = 1,\dots,N \tag{4.3}$$

where λ is the vector of risk premia and a_0 is a vector of constants (Jagannathan, Schaumburg, and Zhou (2010)). Another way to interpret (4.1) is to consider the factor loadings, β_i, as the relationship between the risk factors, f_t, and the returns, R_t. Then λ can be interpreted as the price of risk or the amount of compensation that investors require for holding onto assets with the risk factors present. If λ is positive and significant, then we would say that the factor is priced because it does explain the variation in the cross section of asset prices.

Classic articles by Chen, Roll, and Ross (1986) and Fama and French (1993) use linear factor models to explain the cross sections of assets, each with their own risk factors. While Chen, Roll, and Ross (1986) use macroeconomic variables in their analysis, Fama and French (1993) create mimicking portfolios that capture the pervasive risks presented by firm characteristics such as firm size and book-to-market effects. Along with these two factors, the authors also use the market portfolio in excess of the risk-free rate to create the Fama-French factors, which are now commonly used in empirical studies as they do indeed account for much of the variation in the cross section of security returns.

4.4 Estimation Methods

There are many methods for estimating the risk premia of multifactor asset pricing models. For the purposes of this analysis, I focus on two cross-sectional regression techniques and two generalized method of moments procedures. The first is the simplest and most robust, cross-sectional regression which I have previously used in Chapters 2 and 3 for the estimation of various measures of political risk.

4.4.1 Cross-Sectional Regression

4.4.1.1 The Fama-MacBeth Technique

Cross-sectional regression estimation is based on the Fama-MacBeth technique developed in Fama and MacBeth (1973) to assess the relationship between expected returns and factor betas (Jagannathan, Skoulakis, and Wang (2010)). The first pass is a time series regression to estimate the relationship between the returns and the factor loadings (betas). The second pass estimates a separate risk premium at each time period using the full cross section of betas. The Fama-MacBeth risk premium estimate is then a time-series average of those individual risk premia.

Consider the following reinterpretation of the beta representation (I follow the notation of Jagannathan, Skoulakis, and Wang (2010)):

$$E[R_t] = a_0 1_N + B\lambda = Xc \tag{4.4}$$

where

$$X = [1_N \quad B], \quad c = [a_0 \quad \lambda']', \tag{4.5}$$

X is a N x $(K+1)$ matrix and c is a $(K+1)$ vector of risk premia. $\hat{c}$ is then estimated at each time interval

$$\hat{c}_t = (\hat{X}_T'\hat{X}_T)^{-1}\hat{X}_T' R_t, \quad t = 1, \ldots, T, \tag{4.6}$$

where $\hat{X}_T = [1_N \quad \hat{B}_T]$. The estimate $\hat{c}$ is the average of the full set of T estimates

$$\bar{\hat{c}} = \frac{1}{T}\Sigma_{t+1}^{T}\hat{c}_t. \tag{4.7}$$

4.4.1.2 Ordinary Least Squares

Two-pass regression is essentially the same estimation technique as Fama-MacBeth estimation, only in a slightly different form. Similar to Fama-MacBeth, the first pass is a time series regression to estimate the relationship between the returns and the factor loadings (betas). The second, however, is a cross-sectional regression to measure the relationship between the factor loadings and average returns. Unlike Fama-MacBeth, cross-sectional regression estimates a single $\hat{c}$ over the full time series using an average of the returns for each cross section. Standard OLS estimation of c yields

$$c = (X'X)^{-1}X'E[R_t]. \tag{4.8}$$

Since it is performed in two passes, cross-sectional regression using OLS is generally referred to as “two-pass regression". Both forms yield identical results for $\hat{c}$ and $Var(\hat{c})$ making them equivalent and interchangeable estimation methods (Kleibergen (2009) and Jagannathan, Skoulakis, and Wang (2010)). (Note that Kleibergen (2009) uses demeaned excess returns and factors to first estimate $\hat{\beta}$, then the estimated betas and the average values of returns to estimate $\hat{\lambda}$. This method is similarly prescribed by Jagannathan, Skoulakis, and Wang (2010).)

Regression can be performed either with or without the constant a_0. Per theory, this vector should equal the zero-vector. If regression is run allowing for estimation of the constant, then the parameter can be tested for significance, or it can be suppressed altogether assuming a true null hypothesis (Cochrane (2005)). Most researchers prefer to estimate the constant along with the other parameters as a test of model validity. If the model is correctly specified, then $a_0 = 0_N$ (Jagannathan, Schaumburg, and Zhou (2010)). I include the constant parameter in simulations but I do not report those results.

Of course, two-pass estimation is robust and easy to apply in large samples, however it does impose assumptions that are not overly realistic and, the larger problem, the second pass estimation requires the use of an estimated regressor causing the classic error-in-the-variables problem. The standard assumptions for this estimation process include conditional homoskedasticity, which holds when the returns and factors are identical and independently normally distributed (Jagannathan, Schaumburg, and Zhou (2010)). This is a nice assumption because standard t-tests can then be calculated to test the validity of the relevant coefficients. But there is some empirical evidence to indicate that returns are actually heteroskedastic, nonnormally distributed, and even autocorrelated. GMM performs well under these conditions.

4.4.1.3 Generalized Least Squares

The error-in-the-variables problem is not one that can be overlooked. There are several prescribed methods for compensating for this problem. One method is to use portfolios instead of individual stocks as the testing assets. It is believed that the large number of stocks employed are estimated precisely enough to compensate for the error. Another method, suggested by Fama and Macbeth (1973), is to estimate a separate variance matrix accounting for the error in the second stage, however, this method has proven to overstate the precision of estimates and is subsequently inefficient under the assumption of conditional homoskedasticity. And yet another method is to use generalized least squares in the second pass of estimation. c is then formed as

$$c = (X'QX)^{-1}X'QE[R_t] \tag{4.9}$$

where Q is positive definite N x N matrix. With this method, portfolio formation may not even be necessary.

Another less-frequently implemented technique includes weighted least squares in the second pass of estimation. But I focus my analysis on the most common methods. For comparison, I estimate risk premia using both OLS cross-sectional regression and GLS. I analyze both techniques relative to the GMM procedures two-stage and iterative, detailed in the next section. And because of the assumed return, factor, and error properties necessary for least squares estimation, estimates should be robust to standard t-testing and pricing error evaluation. T-statistics are the more popular assessments of model validity using cross-sectional regression estimation, but I do not assess that in this endeavor.

4.4.2 Generalized Method of Moments Estimation

4.4.2.1 GMM Approach

I also examine the cross section of returns using generalized method of moments estimation. This technique is appealing to use under more realistic assumptions because it allows for serial correlation and conditional heteroskedasticity (see Jagannathan, Skoulakis, and Wang (2010)). However, GMM is the most efficient unbiased estimator when returns and factors are homoskedastic and independent. The generalized method of moments is further advantageous because it allows estimations of all model parameters in a single pass eliminating the earlier error-in-the-variables problem. But it should be noted that GMM has been known to overreject models with small sample size and time series compared to other methods of estimation. GMM can be performed using either the linear beta pricing model representation or the stochastic discount factor representation. Both are asymptotically equivalent, so for comparison, I will estimate the empirical model using the linear beta representation.

Consider the vector R_t of excess returns on N assets and f_t the vector of K risk factors, both at time t. The reiteration of the beta restriction is

$$E[R_t] = B\lambda \tag{4.10}$$

dropping the intercept for convenience. If returns follow the process $R_t = \phi + Bf_t + u_t$, then we can substitute the beta restriction through $\phi = E[R_t] - BE[f_t] = B\lambda - BE[f_t]$ into the returns process:

$$R_t = B(f_t - E[f_t] + \lambda) + u_t, \tag{4.11}$$

where B is the vector of factor loadings, $B = E[R_t, (f_t - E[f_t])]Var[f_t]^{-1}$, and the properties of u_t are

$$E[u_t] = 0_N \tag{4.12a}$$

$$E[u_t f_t'] = 0_{NxK} \tag{4.12b}$$

From the above equations the moment restrictions are then

$$E[R_t - B(f_t - E[f_t] + \lambda)] = 0_N \tag{4.13a}$$

$$E[[R_t - B(f_t - E[f_t] + \lambda)]f_t'] = 0_{NxK} \tag{4.13b}$$

$$E[f_t - E[f_t]] = 0_K \tag{4.13c}$$

The last equation identifies the risk premium λ. These three equations combine to formulate the expected value of the moment restriction, or more precisely $E[g(x_t, \theta_0)] = 0_N$ where $\theta = [\delta' \; vec(B)' \; \mu']'$. We then use the sample analogue $g_T(\theta) = \frac{1}{T}\Sigma_{t=1}^{T} g(x_t, \theta)$ to solve

$$\min_{\theta} g_T(\theta)' S_T^{-1} g_T(\theta), \tag{4.14}$$

where S_T is the consistent estimator of the spectral density matrix of $g(x_t, \theta)$, and find the GMM estimator $\hat{\theta}$.

4.4.2.2 Two-Step Estimator

In most applications GMM is performed either in two stages or iteratively, the difference being the number of times the weighting matrix is reestimated. The two-step estimator works by first using an identity matrix to weight the moment conditions so that $\hat{\theta}$ is chosen to minimize

$$\min_{\theta} g_T(\theta)' g_T(\theta) \tag{4.15}$$

(Hansen, Heaton, and Yaron (1996)). Using those initial parameter estimates, another estimate of S_T^{-1} is obtained and once again $\hat{\theta}$ is chosen to minimize

$$\min_{\theta} g_T(\theta)' \hat{S}_T^{-1} g_T(\theta), \tag{4.16}$$

wherein the new estimate of $\hat{\theta}$ contains the estimates of the second stage parameters (Ferson and Foerster (1994)).

4.4.2.3 Iterative Estimator

The iterative estimator continues from the two-step estimator and reestimates S_T^{-1} until $\hat{\theta}$ converges (Hansen, Heaton, and Yaron (1996)). Both methods can be utilized under either the beta model specification or the stochastic discount factor specification with similar results obtained with correct framework for the latter (Jagannathan and Wang (2002)). A third GMM procedure includes the continuously-updating estimator wherein the covariance matrix is repeatedly altered as $\hat{\theta}$ changes. But I choose to compare the more often used two stage estimator and iterative estimator with the cross-sectional methods, OLS and GLS, in estimation of risk premia. Specification tests for the GMM include the J-statistic (the Hansen test) and the Hansen-Jagannathan distance statistic with more overrejections of correctly specified models from the HJ-distance test (Ahn and Gadarowski (2004)). This analysis, however, does not assess these statistics.

4.5 Simulations

To compare the small sample properties of least squares regression with generalized method of moments estimation, I estimate and test the abilities of each with a two-factor model. The simulation process is similar to that of Kan and Zhou (1999). I obtain betas and variances from regression using the 25 monthly portfolios from Kenneth R. French's data library, the political risk factor and excess market return both from Chapter 3, which dates from January 1927 through December 2009 (French (2012)). With these parameters, and prespecified risk premia, I simulate returns to 960 observations in 1,000 draws of each dataset.

Twenty-five excess returns are generated according to the process in equation (4.11) under the beta-pricing restriction in (4.10) with simulations of two factors: the political regime change dummy variable as factor 1 and the Fama-French excess market return as factor 2. The political factor is drawn from the Bernoulli distribution with the probability calibrated to the ratio of democrat to republican regimes from the Chapter 3 sample. To simulate the market factor, I create a zero-mean AR(1) process calibrated to the auto-correlation and volatility of the demeaned market return. The error terms are drawn from a multivariate normal distribution with mean zero and variance matrix set to the covariances of the model residuals obtained from regression in Chapter 3, with zeros for the off-diagonal elements.

For the simulations in Table 4.1, lambda values are set to the actual lambda values obtained from regression using the 25 portfolios at $\lambda_1 = 0.376\%$ and $\lambda_2 = 0.81\%$ for the political factor risk premium and the market factor risk premium, respectively. The table reports the results for ordinary least squares (OLS), generalized least squares (GLS), two-step generalized method of moments (GMM2), and iterated generalized method of moments estimation methods. Reported information includes average lambda values, standard errors, and t-statistics for both λ_1 and λ_2. More importantly, Table 4.1 also reports the rejection rates of the hypothesis of zero risk premium, or an insignificant risk factor. Using t-ratio tests at the 95% confidence interval, I discover the rejection rates of the null hypothesis $H_0 : \lambda_k = 0$ in 1,000 draws for $k = 1, 2$.

Table 4.1: **Power Tests– Rejection Rates of the Null Hypothesis** $H_0 : \lambda_k = 0$

	OLS	**GLS**	**GMM2**	**GMMI**
Testing $H_0 : \lambda_1 = 0$ *when* $\lambda_1 = 0.376\%$				
Average Lambda	0.285	0.274	0.253	0.217
Average Standard Error	0.067	0.065	0.081	0.082
Average T-Statistic	4.416	4.467	4.085	3.985
Rejection Rate	0.907	0.927	0.803	0.773
Testing $H_0 : \lambda_2 = 0$ *when* $\lambda_2 = 0.81\%$				
Average Lambda	0.666	0.686	0.638	0.636
Average Standard Error	0.284	0.276	0.267	0.261
Average T-Statistic	2.420	2.522	2.559	2.547
Rejection Rate	0.597	0.667	0.633	0.643

Using t-ratio tests, this table reports the probability of rejecting $H_0 : \lambda_k = 0$ at the 95% confidence interval in 1,000 simulations. Setting the true values of $\lambda_1 = 0.376\%$ and $\lambda_2 = 0.81\%$, twenty-five returns are generated to 960 observations according to the process:

$$R_{i,t} = \alpha_i + f'_{1,t}\beta_{i,1} + f'_{2,t}\beta_{i,2} + u_{i,t}, \quad t = 1, \ldots, 960, \quad i = 1, \ldots, 25,$$

where errors are multivariate normally distributed and betas and variances are obtained from estimation using actual returns. Factor 1 is the political factor, simulated using the Bernoulli distribution. The second factor is the excess market return, simulated as an AR(1) process. The beta-pricing model places the restriction:

$$E[R_{i,t}] = \lambda'_1\beta_{i,1} + \lambda'_2\beta_{i,2}$$

The table also includes average risk premia, standard errors, and t-statistics.

Results indicate slightly more power from the least squares methods over the GMM methods. In the top panel, a false null is correctly rejected more than 90% of the time for the first risk factor under both least squares methodologies, with generalized leasts squares showing just slightly more power than ordinary least squares. The GMM procedures perform well, but with slightly less power around 80% and larger standard errors. The least squares methods also provide better point estimates, with iterated GMM the furthest in estimation, on average, from the actual value of λ_1. OLS and GLS do not perform too differently from one another nor do the GMM methods from each other.

In the lower panel, which demonstrates the results of estimation of the market factor risk premium, better point estimates are also obtained under least squares regressions. GLS just outperforms OLS in terms of estimates and power. For the market factor, unlike the political factor, the GMM estimators perform better than ordinary regression, however, GLS maintains the larger power of all four methodologies. Though the average lambda values are closer to the actual lambda value under least squares estimation for the second risk factor, standard errors are smaller under GMM. In terms of power and point estimates, generalized least squares outperforms the other estimation procedures for factor 2.

Overall, it appears that generalized least squares maintains more power in rejecting a false null hypothesis, however the full table produces inconsistent results for the other estimators. For the political factor, which is nontraded, OLS produces the best point estimate and maintains power just beneath GLS. But for the market factor, a traded factor, OLS maintains the lowest power but better point estimates than either GMM method. The power results of ordinary least squares could be due to the lack of a correction for the error-in-the-variables problem in the second stage of estimation, although previous research indicates that the understatement in standard errors is minimal (Shanken and Zhou (2007)). There is evidence to suggest that GMM does maintain more small sample bias.

Table 4.2 presents the results for size comparisons. The top panel presents the results of estimation when λ_1 is set to zero and the lower panel when λ_2 is set to zero. Using t-ratio tests at the 95% confidence interval, I discover the rejection rates of the null hypothesis $H_0 : \lambda_k = 0$, which is correctly specified. In general, lower rejection rates of a correctly specified null hypothesis are preferred. In Table 4.2, rejection rates are consistently well above 5% for both panels.

In the top panel, point estimates amongst the various estimation methods are not too different from one another. Negative risk premia would imply that investors pay to hold onto an asset with this risk factor present. This is counterintuitive to standard asset pricing theory. But the small estimates of lambda when the true value is zero indicate that while some of the factors may be statistically significant, they are not economically important. Interestingly, standard errors are larger from least squares regressions, although rejection rates are lower. Results indicate that, for factor 1, generalized method of moments procedures tend to overreject a correctly specified null hypothesis more so than regression-based methods.

Table 4.2: **Size Tests– Rejection Rates of the Null Hypothesis** $H_0 : \lambda_k = 0$

	OLS	**GLS**	**GMM2**	**GMMI**
Testing $H_0 : \lambda_1 = 0$ *when* $\lambda_1 = 0$				
Average Lambda	-0.004	0.006	-0.003	-0.009
Average Standard Error	0.057	0.053	0.046	0.048
Average T-Statistic	-0.074	0.087	-0.052	-0.209
Rejection Rate	0.250	0.273	0.357	0.377
Testing $H_0 : \lambda_2 = 0$ *when* $\lambda_2 = 0$				
Average Lambda	-0.110	-0.095	-0.116	-0.158
Average Standard Error	0.282	0.274	0.268	0.270
Average T-Statistic	-0.439	-0.400	-0.587	-0.658
Rejection Rate	0.157	0.217	0.213	0.187

Using t-ratio tests, this table reports the probability of rejecting $H_0 : \lambda_k = 0$ at the 95% confidence interval in 1,000 simulations. Two separate models are evaluated within this table: the top panel sets $\lambda_1 = 0$, the bottom panel sets $\lambda_2 = 0$. Twenty-five returns are generated to 960 observations according to the process:

$$R_{i,t} = \alpha_i + f'_{1,t}\beta_{i,1} + f'_{2,t}\beta_{i,2} + u_{i,t}, \quad t = 1, \dots, 960, \quad i = 1, \dots, 25,$$

where errors are multivariate normally distributed and betas and variances are obtained from estimation using actual returns. Factor 1 is the political factor, simulated using the Bernoulli distribution. The second factor is the excess market return, simulated as an AR(1) process. The beta-pricing model places the restriction:

$$E[R_{i,t}] = \lambda'_1\beta_{i,1} + \lambda'_2\beta_{i,2}$$

The table also includes average risk premia, standard errors, and t-statistics.

The lower panel, once again, produces incongruent results. OLS generates lower rejection rates, but interestingly, iterated GMM does not perform that far behind. While risk premia are still, in general, negative, these values are larger and more problematic in terms of estimation of false factors. This indicates that one must use caution in the determination of risk factors. All four estimation methods can wrongly reject a correct null hypothesis and produce risk premia estimates of consequence. This highlights the importance of discovering risk factors not only based on statistical methodologies but economic theory.

4.6 Conclusion

Using ordinary least squares, generalized least squares, two stage generalized method of moments, and iterated generalized method of moments estimation procedures, I estimate and test the small sample properties of each with a two factor model. I generate twenty-five excess returns using factors simulated to mimic the political regime change dummy factor and excess market return factor from Chapter 3. In terms of power and point estimates, I find that the least squares regressors, ordinary and generalized, outperform the generalized method of moments estimators, two-step and iterated. While, in general, the least squares methods are preferred to GMM, GLS tends to perform better than OLS for power, however, ordinary least squares delivers better point estimates. Both generalized method of moments procedures exhibit lower power and more bias in estimates, supporting the argument that GMM displays small sample bias.

While all methodologies demonstrate capabilities in rejecting a false null hypothesis, all methods, in turn, also incorrectly reject a true null, with perhaps ordinary least squares demonstrating the least tendency to overreject (as previously suggested, the generalized methods continue to overreject a correctly specified model). This indicates the need to exercise caution in the determination of risk factors. To find true risk factors, it is important to base analysis on economic theory and not statistical properties alone. Point estimates are reassuring in this sense because while factors may be found to be statistically significant, they are economically meaningless.

The results obtained could be attributed to several influences. First, it is possible that the results from ordinary least squares regression understate the true standard errors, as this estimation procedure does not account for the error-in-the-variables problem. Although it has been shown that the understatement would only be slight (Shanken and Zhou (2007)). It also possible that because the simulated error terms are generated as i.i.d. this would make OLS the more efficient estimator. Perhaps if the error terms were simulated to allow for heteroskedasticity results would differ. Finally, the length of the time series (equivalent to 960 months or 80 years, in this case) and the number of portfolios may affect the performance of all estimation methods. An experiment with fewer portfolios and smaller time series could either exacerbate results or refine them. All of these possible influencers should be investigated in future research endeavors.

Chapter 5

Conclusion

It is generally accepted that political events, decisions, and actions have an effect on the economy and, particularly, financial markets. I hypothesize that political risk, the result of uncertainty over the costs of political outcomes, contributes significantly and positively to asset prices. Using two different measures of political risk, I find support for the argument that political risk cannot be ignored in the pricing of securities. I further analyze the most commonly used techniques to estimate risk premia in linear factor models. I find that, in simulations, regression-based techniques perform better in smaller samples than generalized method of moments procedures. But in actual data, there is little performance difference amongst the four estimators, ordinary least squares, generalized least squares, two stage generalized method of moments, and iterated generalized method of moments.

It has been argued that terrorism is suggestive of alterations in the deeper economic fundamentals, and it is in this context that I analyze terrorism risk, as representative of political risk. According to both cross-sectional regression analysis and generalized method of moments estimation techniques, terrorism risk is systematic and priced in the American financial market from January 1971 to December 2010 for nonindustry returns. However results contrast when the data is separated into time periods before and after September 11, 2001, with the latter period indicating no terrorism risk present. In terms of the contributors to terror, I have determined that social parameters like education and democracy variables contribute more to terror than economic variables like income and employment rates. I further determined that the geographic location of a country positively contributes to terror. If terrorism is in fact suggestive of underlying political unrest, then examination of the determinants of terrorism is important because it is another means by which to mitigate future terror attack risk. Another avenue for future research could be discovery of the complete list of terrorism determinants and the incorporation of the contributing socioeconomic variables in asset pricing models.

I also evaluated a variable that measures regime change, or the change from the Republican Party's control of the lawmaking portion of the federal government to Democrat, as a proxy for political risk. I analyze the average excess returns when the federal government is under the control of each respective party in the time period from 1927 through 2009. I find that averages are larger under a Democratic regime. I then generated a dummy variable to account for the change of regime, or government control, and I discovered that for the 25 portfolios the regime change variable, in the presence of the Fama-French factors, is a priced risk factor. But results were not the same for the 49 industry portfolios. In fact, when combined with the Fama-French factors, the regime change variable was the only valid risk factor implying that this variable requires more compensation for risk than factors related to firm characteristics and is thus more important in the pricing of industry assets than the other factors.

All risk premia were estimated using regression-based and nonlinear estimation techniques. I analyze which method, OLS, GLS, two-step GMM, and iterative GMM, performs better in small samples. Using monte carlo simulations, I generate twenty-five returns from a two-factor model: the political regime change dummy factor and excess market return factor, both from Chapter 3. I discover that the regression-based methods perform better in smaller samples than the generalized method of moments techniques. Generalized least squares also slightly outperforms ordinary least squares in terms of rejection rates, however, OLS produces better point estimates. There is little difference between two-step GMM and iterated with both methods exhibiting small sample bias. I further test the abilities of each methodology by setting each risk premium to zero in simulation. I find that all four methods tend to overreject the correctly specified null hypothesis. This indicates the need to exercise caution in the determination of risk factors. To find true risk factors, it is important to base analysis on not only statistical properties but also economic theory.

The discovery of economically significant risk factors is the endeavor of this dissertation. Although both measures of political risk perform well in asset pricing models, there are avenues for future research that would refine the measurement of political uncertainty. A proper mimicking portfolio might also be an avenue for further inspection. It has been shown that mimicking portfolios created to proxy for nontraded factors are more efficient and precise in the pricing of assets than variables that are not also returns (see Balduzzi and Robotti (2008), Balduzzi and Robotti (2009), and Hou and Kimmel (2006)). One set of possibilities focuses on the terrorism-aspect of political risk. Using the S&P 500, Karloyi (2007) develops his own set of "terrorism portfolios" and derives two terrorism-related investment strategies: the first is a portfolio of S&P 500 stocks assembled based on terrorism risk scores and the second are terrorism-related risk exposure portfolios. Both of these could be used as a stand-in for terrorism risk and the application is an avenue for future research.

Another alternative variable such as a direct measure of political news as suggested by Pástor and Veronesi (2011) could be utilized. Eldor and Melnick (2004) use measures of news in their discovery of the effect of media coverage on terrorism. Though these alternatives might yield statistically interesting results, an economic model would also need to be developed to further corroborate these results on a theoretical level (see Pástor and Veronesi (2011) and Pástor and Veronesi (2012)). Robust assessment methods, such as the use of time-varying betas or conditional linear factor models, could also yield interesting results.

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Appendix A

Summary Statistics for the Terror Events Panel by Region

Region	Total	Yearly Avg	Std Dev	Min	Max
North America	836	14.667	21.113	0	95
CentralAmerica & Caribbean	1877	7.599	36.022	0	500
South America	6568	28.807	93.146	0	659
East Asia	373	9.816	18.531	0	93
Southeast Asia	3628	21.216	49.999	0	320
South Asia	10152	76.331	114.095	0	666
Central Asia	214	2.816	7.355	0	40
Western Europe	3043	8.898	20.280	0	156
Eastern Europe	529	2.320	6.496	0	57
MiddleEast & North Africa	10205	29.839	110.428	0	1104
Sub-Saharan Africa	3829	5.167	19.614	0	272
Russia & Former Soviet	1383	9.099	24.435	0	173
Australasia & Oceania	118	2.070	3.494	0	18
Total	**42755**	**15.204**	**59.479**	**0**	**1104**

Summary Statistics for the Terror Events Panel by Country

Country	Total	Yearly Avg	Std Dev	Min	Max
North America					
Canada	34	1.789	2.175	0	8
Mexico	298	15.684	26.854	0	95
United States	504	26.526	18.341	0	55
Central America & Caribbean					
Antigua and Barbuda	2	0.105	0.315	0	1
Belize	5	0.263	0.806	0	3
Costa Rica	9	0.474	0.772	0	2
Cuba	30	1.579	3.717	0	14
Dominican Republic	43	2.263	4.039	0	12
El Salvador	753	39.632	119.21	0	500
Guatemala	431	22.684	33.495	0	84
Haiti	172	9.053	11.559	0	34
Honduras	107	5.632	8.18	0	22
Jamaica	21	1.105	2.208	0	8
Nicaragua	196	10.316	19.599	0	80
Panama	90	4.737	10.06	0	41
Puerto Rico	18	0.947	1.87	0	6
South America					
Argentina	165	8.684	12.706	0	41

Summary Statistics for the Terror Events Panel by Country

Country	Total	Yearly Avg	Std Dev	Min	Max
Bolivia	98	5.158	10.383	0	38
Brazil	165	8.684	12.033	0	40
Chile	476	25.053	50.002	0	161
Colombia	3541	186.368	180.198	0	598
Ecuador	89	4.684	5.935	0	23
Guyana	18	0.947	1.545	0	5
Paraguay	27	1.421	3.043	0	12
Peru	1798	94.632	193.115	0	659
Suriname	16	0.842	1.922	0	7
Uruguay	24	1.263	2.621	0	11
Venezuela	151	7.947	11.38	0	41
East Asia					
China	154	8.105	14.456	0	62
Japan	219	11.526	22.152	0	93
Southeast Asia					
Brunei	1	0.53	0.229	0	1
Cambodia	240	12.632	20.63	0	67
Indonesia	454	23.895	27.09	0	87
Laos	15	0.789	1.619	0	6
Malaysia	13	0.684	1.057	0	3

Summary Statistics for the Terror Events Panel by Country

Country	Total	Yearly Avg	Std Dev	Min	Max
Myanmar	163	8.579	9.02	0	35
Philippines	1691	89	82.537	0	320
Thailand	1041	54.789	86.305	0	292
South Asia					
Vietnam	10	0.526	1.02	0	4
Afghanistan	1516	79.789	124.995	0	398
Bangladesh	597	31.421	39.382	0	161
Bhutan	4	0.211	0.713	0	3
India	3543	186.474	115.894	0	520
Nepal	461	24.263	30.446	0	100
Pakistan	2849	149.947	177.586	0	666
Sri Lanka	1182	62.211	50.358	0	175
Central Asia					
Kazakhstan	9	0.474	1.02	0	4
Kyrgyzstan	21	1.105	1.56	0	5
Tajikistan	165	8.684	12.992	0	40
Uzbekistan	19	1	2.108	0	8
Western Europe					
Austria	44	2.316	3.417	0	12

Summary Statistics for the Terror Events Panel by Country

Country	**Total**	**Yearly Avg**	**Std Dev**	**Min**	**Max**
Belgium	43	2.263	2.806	0	9
Denmark	14	0.739	1.628	0	6
Finland	5	0.263	0.452	0	1
France	310	16.316	15.829	0	50
Germany	554	29.158	49.141	0	156
Greece	465	24.474	17.902	0	59
Iceland	1	0.053	0.229	0	1
Ireland	60	3.158	4.113	0	16
Italy	171	9	9.713	0	37
Luxembourg	4	0.211	0.713	0	3
Netherlands	55	2.895	3.446	0	12
Norway	11	0.579	0.838	0	2
Portugal	6	0.316	0.82	0	3
Spain	938	49.368	31.434	0	113
Sweden	40	2.105	3.071	0	12
Switzerland	31	1.632	1.77	0	6
United Kingdom	291	15.316	20.144	0	76
Eastern Europe					
Albania	70	3.684	9.499	0	42
Bosnia-Herzegovina	145	7.632	11.917	0	42
Bulgaria	36	1.895	2.826	0	12

Summary Statistics for the Terror Events Panel by Country

Country	Total	Yearly Avg	Std Dev	Min	Max
Croatia	48	2.526	5.591	0	24
Czech Republic	16	0.842	1.344	0	4
Hungary	40	2.105	4.689	0	17
Macedonia	96	5.053	12.895	0	57
Moldova	18	0.9474	2.505	0	11
Poland	32	1.684	2.382	0	7
Romania	5	0.263	0.562	0	2
Slovak Republic	17	0.895	1.524	0	5
Slovenia	6	0.316	0.749	0	3
MiddleEast & North Africa					
Algeria	1673	88.053	93.545	0	339
Cyprus	53	2.789	4.036	0	11
Egypt	435	22.895	41.188	0	143
Iran	162	8.526	9.605	0	43
Iraq	4132	217.474	379.466	0	1104
Israel	857	45.105	35.851	0	131
Jordan	42	2.211	2.679	0	11
Kuwait	31	1.632	3.515	0	15
Lebanon	652	34.316	31.28	0	91
Libya	8	0.421	0.961	0	4
Morocco	20	1.053	1.81	0	6

Summary Statistics for the Terror Events Panel by Country

Country	Total	Yearly Avg	Std Dev	Min	Max
Qatar	4	0.211	0.419	0	1
Saudi Arabia	48	2.526	4.274	0	18
Syria	9	0.474	0.841	0	3
Tunisia	12	0.632	0.895	0	3
Turkey	1889	99.421	135.433	0	515
United Arab Emirates	3	0.158	0.501	0	2
Yemen	175	9.211	7.48	0	25
Sub-Saharan Africa					
Angola	414	21.789	46.854	0	206
Benin	9	0.474	0.905	0	3
Botswana	2	0.105	0.315	0	1
Burkina Faso	2	0.105	0.459	0	2
Burundi	348	18.316	24.125	0	83
Cameroon	21	1.105	1.997	0	6
Central African Republic	12	0.632	1.012	0	4
Chad	40	2.105	2.923	0	11
Djibouti	14	0.737	1.447	0	6
Eritrea	7	0.368	0.761	0	2
Ethiopia	83	4.368	3.847	0	13
Gabon	3	0.158	0.375	0	1
Gambia	3	0.158	0.375	0	1

Summary Statistics for the Terror Events Panel by Country

Country	Total	Yearly Avg	Std Dev	Min	Max
Ghana	16	0.842	2.007	0	8
Guinea	10	0.526	1.073	0	4
Guinea-Bissau	7	0.368	0.955	0	4
Kenya	100	5.263	7.519	0	30
Lesotho	4	0.211	0.713	0	3
Liberia	27	1.421	2.388	0	10
Madagascar	20	1.053	1.957	0	7
Malawi	4	0.211	0.713	0	3
Mali	45	2.368	4.003	0	13
Mauritania	5	0.263	0.562	0	2
Mozambique	86	4.526	9.851	0	35
Namibia	30	1.579	4.623	0	20
Niger	50	2.632	4.179	0	16
Nigeria	288	15.158	21.096	0	76
Rwanda	132	6.947	11.043	0	33
Senegal	85	4.474	6.670	0	26
Sierra Leone	88	4.632	6.491	0	22
Somalia	512	26.947	49.793	0	167
South Africa	866	45.579	77.695	0	272
Sudan	142	7.474	8.940	0	32
Swaziland	11	0.579	0.769	0	3
Tanzania	7	0.368	0.496	0	1

Summary Statistics for the Terror Events Panel by Country

Country	**Total**	**Yearly Avg**	**Std Dev**	**Min**	**Max**
Togo	45	2.368	6.660	0	27
Uganda	241	12.684	9.256	0	30
Zambia	25	1.316	2.518	0	8
Zimbabwe	25	1.316	1.887	0	6
Russia & Former Soviet					
Azerbaijan	38	2.000	3.399	0	12
Belarus	7	0.368	0.597	0	2
Estonia	13	0.684	1.455	0	6
Georgia	163	8.579	10.854	0	39
Latvia	16	0.842	1.119	0	4
Lithuania	8	0.421	0.838	0	3
Russia	1107	58.263	43.57	0	173
Ukraine	31	1.632	2.499	0	10
Australasia & Oceania					
Australia	46	2.421	2.694	0	9
New Zealand	15	0.789	1.316	0	5
Papua New Guinea	57	3.000	5.121	0	18

Appendix B

Years of Government Control Based on Regime

Regime Control	**Democrat**	**Years**	**Republican**	**Years**
1. Controls Executive Branch*	1933-1952; 1961-1968; 1977-1980; 1993-2000; 2009	41	1927-1932; 1953-1960; 1969-1976; 1981-1992; 2001-2008	43
2. Controls Legislative Branch**	1933-1946; 1949-1952; 1955-1980; 1987-1994; 2007-2009	55	1927-1932; 1947-1948; 1953-1954; 1995-2006	23
3. Controls both branches***	1933-1946; 1949-1952; 1961-1968; 1977-1980; 1993-1994; 2009	33	1927-1932; 1953-1954; 1981-1986; 2001-2008	23

*Controls the White House only. **Controls both houses of Congress, the Senate and the House of Representatives. ***Controls the White House and at least one house of Congress. Control indicates the party with the majority elected seats in the house irrespective of what party is in control of the remaining houses.

Average Excess Returns– *Executive Branch Control*

Democrat

Annual	Average Return	Variance	Std Error	t-Statistic	Population Avg
25 Portfolios	18.324	887.852	0.931	7.537	11.31
49 Industry	15.211	907.083	0.735	7.442	9.744
Mkt Return	12.822	331.884	2.845	1.722	7.924
Monthly					
25 Portfolios	1.445	67.474	0.074	8.432	0.82
49 Industry	1.172	56.702	0.053	8.707	0.71
Mkt Return	1.015	27.461	0.236	1.716	0.61
Annualized					
25 Portfolios	17.34	735.537	0.847	8.847	9.846
49 Industry	14.059	703.804	0.647	8.561	8.52
Mkt Return	12.184	303.436	2.72	1.789	7.318

Republican

Annual	Average Return	Variance	Std Error	t-Statistic	Population Avg
25 Portfolios	4.462	850.59	0.9	-7.608	11.31
49 Industry	4.407	933.318	0.736	-7.249	9.744
Mkt Return	3.142	514.531	3.5	-1.366	7.924
Monthly					
25 Portfolios	0.211	66.667	0.073	-8.381	0.82
49 Industry	0.259	60.454	0.054	-8.331	0.71
Mkt Return	0.214	32.218	0.253	-1.566	0.61
Annualized					
25 Portfolios	2.53	1544.047	1.213	-6.033	9.846
49 Industry	3.112	1040.318	0.777	-6.957	8.52
Mkt Return	2.567	467.446	3.336	-1.424	7.318

Average Excess Returns– *Legislative Branch Control*

Democrat

Annual	Average Return	Variance	Std Error	t-Statistic	Population Avg
25 Portfolios	13.752	986.402	0.847	2.884	11.31
49 Industry	11.598	972.886	0.657	2.823	9.744
Mkt Return	9.089	419.484	2.762	0.422	7.924
Monthly					
25 Portfolios	1.035	59.354	0.060	3.577	0.82
49 Industry	0.852	53.903	0.045	3.174	0.71
Mkt Return	0.698	26.573	0.201	0.438	0.61
Annualized					
25 Portfolios	12.42	846.836	0.785	3.280	9.846
49 Industry	10.22	812.46	0.6	2.832	8.52
Mkt Return	8.373	395.606	2.682	0.393	7.318

Republican

Annual	Average Return	Variance	Std Error	t-Statistic	Population Avg
25 Portfolios	5.796	869.257	1.257	-4.386	11.31
49 Industry	5.826	1002.502	1.054	-3.716	9.744
Mkt Return	5.744	584.379	5.154	-0.423	7.924
Monthly					
25 Portfolios	0.315	99.441	0.123	-4.120	0.82
49 Industry	0.396	77.8	0.085	-3.708	0.71
Mkt Return	0.437	41.813	0.398	-0.433	0.61
Annualized					
25 Portfolios	3.778	2295.698	2.043	-2.970	9.846
49 Industry	4.747	1261.453	1.183	-3.190	8.52
Mkt Return	5.248	510.647	4.818	-0.430	7.318

Average Excess Returns– *Both Branches Control*

Democrat					
Annual	Average Return	Variance	Std Error	t-Statistic	Population Avg
25 Portfolios	20.321	1011.864	1.107	8.137	11.31
49 Industry	16.563	992.527	0.856	7.962	9.744
Mkt Return	13.005	363.21	3.318	1.532	7.924
Monthly					
25 Portfolios	1.593	75.727	0.087	8.827	0.82
49 Industry	1.269	60.587	0.061	9.144	0.71
Mkt Return	1.032	29.387	0.272	1.550	0.61
Annualized					
25 Portfolios	19.110	848.408	1.014	9.135	9.846
49 Industry	15.223	770.137	0.754	8.885	8.520
Mkt Return	12.383	338.036	3.201	1.583	7.318
Republican					
Annual	Average Return	Variance	Std Error	t-Statistic	Population Avg
25 Portfolios	2.744	921.953	1.295	-6.616	11.31
49 Industry	2.73	1060.954	1.085	-6.467	9.744
Mkt Return	1.09	623.595	5.324	-1.284	7.924
Monthly					
25 Portfolios	0.032	97.363	0.121	-6.491	0.82
49 Industry	0.11	78.208	0.085	-7.054	0.71
Mkt Return	0.048	42.532	0.401	-1.400	0.61
Annualized					
25 Portfolios	0.385	2367.045	2.075	-4.560	9.846
49 Industry	1.325	1361.893	1.229	-5.855	8.52
Mkt Return	0.575	583.273	5.149	-1.309	7.318

Appendix C

Years of Government Control Based on the Regime Change Dummy Variable

Regime Control	Democrat(0)	Years	Republican(1)	Years
Controls both branches*	1933-1946; 1949-1952; 1955-1980; 1987-1993; 2007-2009	54	1927-1932; 1947-1948; 1953-1954; 1981-1986; 1994-2006	29

*Controls the White House and at least one house of Congress. Control indicates the party with the majority elected seats in the house.

Average Excess Returns Under the Regime Change Dummy Variable

Democrat(0)

Annual	Average Return	Variance	Std Error	t-Statistic	Population Avg
25 Portfolios	14.111	997.127	0.859	3.260	11.31
49 Industry	11.927	983.341	0.666	3.275	9.744
Mkt Return	9.343	423.761	2.801	0.507	7.924
Monthly					
25 Portfolios	1.062	60.23	0.061	3.963	0.82
49 Industry	0.876	54.563	0.045	3.664	0.71
Mkt Return	0.717	26.899	0.204	0.526	0.61
Annualized					
25 Portfolios	12.746	856.182	0.796	3.641	9.846
49 Industry	10.513	821.076	0.609	3.272	8.52
Mkt Return	8.604	400.071	2.722	0.473	7.318

Republican(1)

Annual	Average Return	Variance	Std Error	t-Statistic	Population Avg
25 Portfolios	6.092	726.012	1.001	-5.214	11.31
49 Industry	5.679	861.188	0.851	-4.776	9.744
Mkt Return	5.281	483.728	4.084	-0.647	7.924
Monthly					
25 Portfolios	0.371	80.575	0.096	-4.675	0.82
49 Industry	0.401	66.567	0.068	-4.527	0.71
Mkt Return	0.41	35.803	0.321	-0.622	0.61
Annualized					
25 Portfolios	4 .447	1794.462	1.573	-3.432	9.846
49 Industry	4.81	1037.469	0.934	-3.972	8.52
Mkt Return	4.922	420.064	3.806	-0.629	7.318